Are Face Detection Models Biased?

Surbhi Mittal¹, Kartik Thakral¹, Puspita Majumdar¹,², Mayank Vatsa¹ and Richa Singh¹
¹IIT Jodhpur, India, ²IIT Delhi, India

Abstract—The presence of bias in deep models leads to unfair outcomes for certain demographic subgroups. Research in bias focuses primarily on facial recognition and attribute prediction with scarce emphasis on face detection. Existing studies consider face detection as binary classification into ‘face’ and ‘non-face’ classes. In this work, we investigate possible bias in the domain of face detection through facial region localization which is currently unexplored. Since facial region localization is an essential task for all face recognition pipelines, it is imperative to analyze the presence of such bias in popular deep models. Most existing face detection datasets lack suitable annotation for such analysis. Therefore, we web-curate the Fair Face Localization with Attributes (F2LA) dataset and manually annotate more than 10 attributes per face, including facial localization information. Utilizing the extensive annotations from F2LA, an experimental setup is designed to study the performance of four pre-trained face detectors. We observe (i) a high disparity in detection accuracies across gender and skin-tone, and (ii) interplay of confounding factors beyond demography. The F2LA data and associated annotations can be accessed at http://iab-rubric.org/index.php/F2LA.

I. INTRODUCTION

With deep learning models/algorithms becoming the norm of the modern AI systems, it has become essential to evaluate these algorithms (and systems) thoroughly to minimize any adverse impact on the society. The incorporation of bias in the algorithms is one primary issue that has been highlighted in the literature [8], [22]. Research has shown that the performance of deep learning algorithms vary for people with different attributes such as gender and skin-tone subgroups under a variety of settings [2], [17]. For instance, it has recently been observed that the automatic face-cropping algorithm of Twitter favors young and lighter-skinned people over others [23]. With increasing instances of these issues, it is of paramount importance to include fairness as one of the metrics for evaluation of these algorithms.

Fairness of facial analysis algorithms is being studied in the literature for the last few years [15], [20], [21], [22]. Most of the research efforts have been concentrated towards establishing awareness towards bias in face recognition systems and a number of datasets have been proposed for the same [10], [24]. However, limited research work has studied the impact of face detection which forms an important part of the recognition pipeline and failure in which can lead to incorrect decisions (Fig. 1). To the best of our knowledge, none of the existing studies on bias in face detection focus on bounding box localization. As the first contribution of this work, we analyze different facial detectors to understand if they exhibit any biased behavior.

Fig. 1. Face detection models failing to detect faces.

The presence of bias in deep models has been attributed to non-demographic factors (such as variation in pose, illumination, and image quality), as well as more complex, demographic factors such as race, gender, and skin tone [11]. To study biased behavior, datasets with extensive annotations corresponding to different attributes are required which are lacking in existing databases. To facilitate the study of bias for this research, the second contribution is that we have collected images from the web and curated the Fair Face Localization with Attributes (F2LA) dataset, with annotation of ten attributes per face along with bounding box localization. Using the F2LA database, we perform a detailed analysis on four face detectors and observe that different confounding factors play an important role in decision making.

II. RELATED WORK

Facial analysis models have shown superlative performance over the last few years [4], [6], [7], [14], [28]. However, biased predictions have been reported in various facial analysis tasks such as face detection, attribute prediction, and face recognition. The seminal paper by Buolamwini et al. [5] showed the biased behavior of commercial gender classifiers against darker-skinned females. Over the years, multiple studies have been performed in facial recognition and attribute prediction [16], [22]. However, demographic bias in face detection has received significantly less attention. Datasets containing extensive annotations for demographic subgroups as well as non-demographic attributes are required for studying bias. However, popular benchmark databases for face detection including AFW [30], PASCAL face [26], FDDB [9], and WIDER FACE [27] datasets do not contain annotations pertaining to both demographic and non-demographic factors.
An existing database for evaluation of bias in faces includes the PPB (Public Parliaments Benchmark) dataset [5]. While PPB contains face images of individuals from three African countries and three European countries, the dataset contains samples in constrained settings with only one face per image. Further, limited approaches to mitigate such bias have been proposed. Amini et al. [3] proposed a novel algorithm for mitigating hidden bias in face detection algorithms. The proposed algorithm uses a variational autoencoder to learn the latent structure and the learned latent distributions re-weight the importance of certain data points during training. However, the face detection problem in the paper is formulated as a binary classification problem where each image contained one face. Modern face detection models provide bounding box annotations corresponding to the faces in a given image along with a confidence score for each detected face. The proposed F2LA dataset is an evaluation set containing 1200 images with bounding box localization as well annotations for 10 attributes corresponding to each face for fairness analysis.

III. EXPERIMENTAL DESIGN

In order to quantify bias in face detection, we require a dataset with annotations for bounding box localization as well as for attributes such as demographic subgroups. The proposed Fair Face Localization with Attributes (F2LA) dataset is employed for studying the behavior of face detectors. This section describes the F2LA dataset and details of the experimental protocol designed for analysis.

A. F2LA Dataset

We web-curate the F2LA dataset containing images of people in unconstrained settings. Facial localization information for 1774 faces in 1200 images is manually annotated along with annotations for 10 attributes per face. These attributes include information pertaining to gender, skin tone, apparent age, facial orientation, blur, illumination, color properties, facial hair, occlusion and background information. These attributes assist in evaluating bias present in existing models across various factors, and provide insights into the fairness of face detection algorithms. The F2LA data and associated annotations can be accessed at http://iab-rubric.org/index.php/F2LA.

Data Collection and Properties: The images are collected by crawling the internet for face images with CC-BY licenses. Variation across multiple attributes is ensured during collection. Samples of the dataset are shown in Fig. 2. Besides localizing each face with a bounding box, several other attributes have been annotated. The details of the attributes and their corresponding classes have been specified in Table I.

Data Annotation: Each image is annotated in a two-step fashion as shown in Fig. 4. In the first step, all the faces from an image are cropped and annotated for a set of attributes described in Table I. The first step in the annotation process is face region localization. We used the freely available annotation tool, LabelImg [1] for this purpose. For the next step,
we designed a user interface (UI) to facilitate the annotation of images. 

**Dataset Protocol:** The dataset consists of a total of 1200 images encompassing 1774 faces. The dataset is divided into train and test sets containing 1000 and 200 images with 1486 and 288 faces, respectively. Since the dataset contains ten annotations per face, we attempt to ensure as little skew as possible across the sensitive attributes (gender, skin-tone, age) in the test set. The distribution of faces across these attributes in the test set are shown in Fig. 3.

**B. Experimental Protocol**

We evaluate and estimate the performance and fairness of existing face detectors through two experiments. In the first experiment, the pre-trained models of existing face detectors are utilized. Since face detection models are often used as a part of pre-processing in many applications, the evaluation of pre-trained models aids in the estimation of possibly overlooked bias. This experiment is performed with four pre-trained face detectors, namely, MTCNN [28], BlazeFace [4], DSFD [12], and RetinaFace [6]. To further explore the prevalence of bias, we perform the second experiment in which we apply a transfer learning approach. This experiment is performed to estimate performance improvement of existing face detectors on the proposed dataset. For this experiment, we employ the popular MTCNN model [28], selected due to its lightweight architecture, suitable for finetuning with 1000 images.

**C. Details of Pre-trained Models**

Four pre-trained face detectors have been used for face detection. While MTCNN uses separate region-proposal and face localization networks, BlazeFace and RetinaFace employ the Single Shot Detector (SSD) design of training one-stage face detection frameworks end-to-end [13].

**Fig. 3.** Distribution of faces across (a) gender, (b) skin-tone, and (c) apparent age attributes on the test set.

---

**Table I**

| Attribute         | Classes                            | Multi-class |
|-------------------|------------------------------------|-------------|
| Gender            | male, female, unsure               | ✓           |
| Skin-tone         | very fair, fair, medium, olive, brown, black, unsure | ✓           |
| Apparent Age      | child, young, middle, old, unsure  | ✓           |
| Blur              | partial, heavy, no blur            | ✓           |
| Illumination      | dim, bright, normal                | ✓           |
| Facial Orientation| frontal, semi-frontal, profile     | ✓           |
| Facial Hair       | mustache, goatee, beard, no facial hair | ✓           |
| Occlusion         | eyes, forehead, mouth, nose, chin, cheek(s), facial boundary | ✓           |
| Background        | plain, crowded, in-focus, out-of-focus | ✓           |
| Color Properties  | grayscale, RGB                     | ✓           |

MTCNN [28]: The MTCNN model is one of the earliest and most popular face detectors. It consists of three lightweight models namely P-Net, R-Net and O-Net used for region proposal refinement, bounding box localization and landmark localization, respectively.

BlazeFace [4]: The BlazeFace model is designed by Google to be a lightweight model suitable for GPU inference in mobiles. Its wide applicability makes it an essential candidate for evaluation. The pre-trained model used in this work is made available by Google’s MediaPipe.

RetinaFace [6]: The RetinaFace detector used extra supervision through facial landmarks and employed self-supervised learning in addition to traditional bounding box regression. It is among the most widely implemented single-stage face detection technique.

DSFD [12]: The DSFD detector utilizes a Feature Enhance Module in addition to the single-shot detection of SSD models. It is among the best performing face detection models on several benchmark databases.

**D. Evaluation Metrics**

For evaluating the performance of the detectors, we calculate the detection accuracy. The detection accuracy for a set is computed as the ratio of correctly detected faces and the total number of faces in the set. A face is considered to be detected correctly if the predicted bounding box localization overlaps with the ground-truth annotation. This overlap is calculated using the IoU (Intersection over Union) metric. The results are evaluated at multiple IoU thresholds \( t \approx 0.5, 0.6, \) and 0.7. To estimate the disparity in performance across subgroups, we calculate standard deviation of the detection accuracies across the different classes. A high performance gap of the model across different classes will result in a high
Implementation Details: For the pre-trained models, we use an MTCNN model pre-trained on the WIDERFACE dataset. A PyTorch/MXnet implementation of the paper is used. For BlazeFace, a PyTorch version of the model is used. The pre-trained weights for the frontal camera model are used in this paper for evaluation. For inferencing the DSFD detector, we employ an optimized version of the detector implemented in PyTorch. This model is pre-trained on the WIDERFACE dataset. Lastly, the RetinaFace detector used in this work is built with a ResNet50 backbone and also pre-trained on the WIDERFACE dataset. For the fine-tuning experiments, the MTCNN model is used. MTCNN contains the region-proposal refinement network P-Net and the bounding box localization network R-Net. We use the pre-trained P-Net and fine-tune the R-Net. Besides fine-tuning on the entire training set, we also fine-tune the network on three subsets of the train set which are balanced across the gender, skin-tone and apparent age attributes, respectively. All parameters except those of the last fully-connected layer of the R-Net are frozen and the model is trained for 20 epochs on the train set. The Adam optimizer is used with an initial learning rate of 0.001. All the experiments are performed on a workstation with Intel Xeon processor, having 128 GB RAM and an NVIDIA RTX-3090 GPU with 24 GB memory.

IV. EXPERIMENTAL RESULTS AND ANALYSIS
To estimate the bias present in different face detection models, we study their performance on gender, skin-tone and apparent age attributes present in the F2LA dataset. We further analyze some of the factors impacting the performance of the pre-trained detectors.

A. Performance of Deep Models
The pre-trained face detection models are evaluated across different demographic subgroups on the F2LA dataset. For gender subgroups, the performance of the four pre-trained models has been provided in Table II. At IoU threshold $t=0.5$,  

![Fig. 5. Bar graph summarizing the performance of models across (a) age and (b) skin tone. The top row corresponds to $t=0.6$ and bottom row to $t=0.7$.](image-url)
TABLE IV

| Attribute | t = 0.5 | t = 0.6 |
|-----------|---------|---------|
| Age       | Skin-tone | Gender | Age       | Skin-tone | Gender |
| Disparity | 5.10     | 4.36    | 5.85      | 3.72      | 6.54    | 8.68   |

**TABLE V**

| Orientation | MTCNN | BlazeFace | DSFD | RetinaFace |
|-------------|-------|-----------|------|------------|
| Frontal     | 65.85 | 53.66     | 92.68| 81.71      |
| Profile     | 36.00 | 20.00     | 80.00| 76.00      |
| Semi-frontal| 61.62 | 44.44     | 92.93| 85.86      |
| Disparity   | 13.19 | 14.20     | 6.04 | 4.04       |

**TABLE V**

| Illumination | MTCNN | BlazeFace | DSFD | RetinaFace |
|--------------|-------|-----------|------|------------|
| Bright       | 57.14 | 50.00     | 92.86| 92.86      |
| Dim          | 44.00 | 32.00     | 92.00| 92.00      |
| Normal       | 63.86 | 49.00     | 91.57| 81.12      |
| Disparity    | 8.25  | 8.26      | 0.54 | 2.24       |

A major boost in performance (>20%) is observed after fine-tuning the model with F2LA’s complete training set as shown in Table III. However, the disparity in performance across gender persists. Further, from Table IV, we observe that these disparities exist for other demographic subgroups such as skin-tone and age as well. On fine-tuning using an age-balanced split, we observe that the disparity reduces from 6.13% to 3.16% at t=0.7. Similarly, across the skin-tone subgroups, we observe a significant reduction in disparity from 8.44% to 5.60% with a skin-balanced fine-tuning of the network. While balanced training reduces the disparity in certain cases, a large gap in performance across subgroups still persists.

**B. Analysis**

In this section, we study the impact of different factors on the performance of the face detection models. Fig. 6 presents some of the samples missed by the BlazeFace, MTCNN and RetinaFace models.

**Role of Demography:** We observe that some detection models perform poorly over certain demographic subgroups (Refer Table II and Figure 5). For example, the MTCNN model performs poorly on individuals belonging to old and male subgroup (Fig. 6(b)). Similar observations have been made for the BlazeFace model (Fig. 6(a)).
Role of Other Confounding Factors: While analyzing results from the pre-trained models, we observe that the MTCNN and BlazeFace models fail to detect faces on grayscale images. Some samples are shown in Fig. 6(a) and (b). Further, the BlazeFace model fails to generalize on large faces (Fig. 6(c)). Conversely, the RetinaFace model fails to detect small faces in an image. We observe factors such as illumination and occlusion may play an important role in face detection. Further, factors such as illumination and occlusion may play an important role in face detection. We observe disparate performance of the pre-trained models across the facial orientation and illumination attributes in Table V. Faces present with high illumination and frontal orientation are easily detected compared to those which are dimly illuminated and have profile view.

Distribution of the WIDERFACE dataset: The bias in performance of models is impacted by the data it is trained on. Since the MTCNN, DSFD, and RetinaFace are trained on the same dataset- the WIDER FACE dataset [27], studying the distribution of the dataset offers insight into the performance of the models. The WIDER FACE dataset contains 32,203 images with 393,703 faces with a 40%/10%/50% split for training, validation, and testing. It is a widely popular large-scale dataset containing images under 62 different event categories taken from the WIDER dataset [25]. Each face contains annotations for the following attributes: pose (typical, atypical), occlusion (none, partial, heavy), illumination (normal, extreme), and blur (clear, normal blur, heavy blur). The distribution of the images in the training set are shown in Fig. 7. It is evident from the distribution that the train dataset is skewed towards Typical poses and Normal illumination. The results in Table V showcase higher performance of models for faces with these attributes in the F2LA dataset. Therefore, we can safely deduce that a skew in training data translates into model performance. Further, the interplay between such confounding factors may play a role in the overall fairness of models.

Validity of the IoU metric: On manual inspection of the faces detected by the DSFD and RetinaFace models, it is discovered that these models provided good detection results. So, why do we observe a disparity in Table II? We observe that while ground-truth annotations are done loosely, the predicted bounding boxes are tight (Fig. 8). This leads to a reduction in overlap leading to low performance at threshold $t=0.5$. The threshold $t$ selected for determining ideal overlap can lead to false negatives especially in cases where the area of interest is small, and has been shown to destabilize the performance [18]. The limitations of the box IoU metric have been discussed in the literature where a lack of spatial information (compared to a mask IoU) leads to incorrect predictions [18]. Since the image presented in Fig. 8 contains faces of the male subgroup and the bounding box area is small, the overall performance for males in the test set is severely affected in this context.

\footnote{The Typical pose and Normal illumination attributes correspond to the Frontal facial orientation and Normal illumination attributes in F2LA.}
V. DISCUSSION AND FUTURE WORK

In this research, we attempt to understand when and why face detection algorithms fail. By studying the impact of various factors on existing face detection algorithms, we also strive to ascertain whether face detection models are biased. The observations are as following:

- While we experimentally detect disparate performance, we observe that the interplay of various factors plays an important role. It is imperative to analyze the performance of models in a holistic manner and not draw conclusions solely based on demographic annotation.

- Role of confounding factors such as scale of face, color properties, illumination and pose may be misattributed to gender or other kinds of bias. While evaluating bias, role of non-demographic factors should be evaluated.

- We also note the limitations of the Intersection over Union metric for assessing face detection performance, and advise careful perusal of loosely versus tightly cropped faces in the data. Several variations of IoU focusing on efficient training have been proposed in recent years [19], [29], however, a greater emphasis on IoU as an evaluation metric is also required.

In the future, more effort is required to study face detection bias in a localization setting. We believe that the web-curated F2LA dataset collected across ten attributes for this study can help to broaden the scope for exploring issues in face detection pertaining to various confounding factors, including demography.

VI. ACKNOWLEDGEMENTS

S. Mittal is partially supported by the UGC-Net JRF Fellowship and IBM Fellowship. K. Thakral is partly supported by the PMRF Fellowship. M. Vatsa is partially supported through the Swarnajayanti Fellowship.

REFERENCES

[1] Tblabelimg. git code (2015). https://github.com/tzutalin/labelImg, 2021. Online; accessed 17 September 2021.

[2] ACLU. Amazon’s face recognition falsely matched 28 members of congress with mugshots. https://tinyurl.com/2p87fj4w, 2018. Online; accessed 17 Feb 2022.

[3] A. Amini, A. P. Soleimany, W. Schwarting, S. N. Bhatia, and D. Rus. Uncovering and mitigating algorithmic bias through learned latent structure. In AAAI/ACM Conference on AI, Ethics, and Society, pages 289–295, 2019.

[4] V. Bazarevsky, Y. Kartytynik, A. Vakunov, K. Raveendran, and M. Grundmann. Blazeface: Sub-millisecond neural face detection on mobile gpus. arXiv preprint arXiv:1907.00407, 2019.

[5] J. Buolamwini and T. Gebru. Gender shades: Intersectional accuracy disparities in commercial gender classification. In Conference on fairness, accountability and transparency, pages 77–91. PMLR, 2018.

[6] J. Deng, J. Guo, E. Ververas, I. Kotsia, and S. Zafeiriou. Retinaface: Single-shot multi-level face localisation in the wild. In IEEE/CVF conference on Computer Vision and Pattern Recognition, pages 5203–5212, 2020.

[7] J. Deng, J. Guo, J. Yang, N. Xue, I. Kotsia, and S. Zafeiriou. Arcface: Additive angular margin loss for deep face recognition. IEEE Transactions on Pattern Analysis and Machine Intelligence, 44(10):5962–5979, 2022.

[8] P. Drozdowski, C. Rathgeb, A. Dantcheva, N. Damer, and C. Busch. Demographic bias in biometrics: A survey on an emerging challenge. IEEE Transactions on Technology and Society, 1(2):89–103, 2020.

[9] V. Jain and E. Learned-Miller. Fddb: A benchmark for face detection in unconstrained settings. Technical report, UMass Amherst technical report, 2010.

[10] K. Karkkainen and J. Joo. Fairface: Face attribute dataset for balanced race, gender, and age for bias measurement and mitigation. In IEEE/CVF Winter Conference on Applications of Computer Vision, pages 1548–1558, 2021.

[11] A. Kortylewski, B. Egger, A. Schneider, T. Gerig, A. Morel-Forster, and T. Vetter. Analyzing and reducing the damage of dataset bias to face recognition with synthetic data. In IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops, pages 0–0, 2019.

[12] J. Li, Y. Wang, C. Wang, Y. Tai, J. Qian, J. Yang, C. Wang, J. Li, and F. Huang. Dfd: dual shot face detector. In IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 5060–5069, 2019.

[13] W. Liu, D. Anguelov, D. Erhan, C. Szegedy, S. Reed, C.-Y. Fu, and A. C. Berg. Ssd: Single shot multibox detector. In European Conference on Computer Vision, pages 21–37. Springer, 2016.

[14] A. Majumdar, R. Singh, and M. Vatsa. Face verification via class sparsity based supervised encoding. IEEE Transactions on Pattern Analysis and Machine Intelligence, 39(6):1273–1280, 2017.

[15] P. Majumdar, S. Mittal, R. Singh, and M. Vatsa. Unravelling the effect of image distortions for biased prediction of pre-trained face recognition models. In IEEE/CVF International Conference on Computer Vision, pages 4133–4141, 2021.

[16] ProPublica. Machine bias. https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing, 2016. Online; accessed 17 Feb 2022.

[17] R. Singh, A. Agarwal, M. Singh, S. Nagpal, and M. Vatsa. On the robustness of face recognition algorithms against attacks and bias. AAAI Conference on Artificial Intelligence, 34(09):13583–13589, 2020.

[18] R. Singh, P. Majumdar, S. Mittal, and M. Vatsa. Unravelling the effect of image distortions for unbiased model prediction. In IEEE/CVF International Conference on Computer Vision, pages 658–666, 2019.

[19] J. Robinson, G. Livitz, Y. Henon, C. Qin, Y. Fu, and S. Timoner. Face recognition: too biased, or not too biased? In IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops, pages 0–1, 2020.

[20] R. Singh, A. Agarwal, M. Singh, S. Nagpal, and M. Vatsa. On the robustness of face recognition algorithms against attacks and bias. AAAI Conference on Artificial Intelligence, 34(09):13583–13589, 2020.

[21] H. Rezatofighi, N. Tsoi, I. Reid, and S. Savarese. Generalized intersection over union: A metric and a loss for bounding box regression. In IEEE conference on computer vision and pattern recognition, pages 658–666, 2019.

[22] R. Singh, A. Agarwal, M. Singh, S. Nagpal, and M. Vatsa. On the robustness of face recognition algorithms against attacks and bias. AAAI Conference on Artificial Intelligence, 34(09):13583–13589, 2020.

[23] R. Singh, P. Majumdar, S. Mittal, and M. Vatsa. Unravelling the effect of image distortions for unbiased model prediction. In IEEE/CVF International Conference on Computer Vision, pages 4133–4141, 2021.

[24] M. Wang, W. Deng, J. Hu, X. Tao, and Y. Huang. Racial faces in the wild: Reducing racial bias by information maximization adaptation network. In IEEE/CVF International Conference on Computer Vision, pages 692–702, 2019.

[25] J. Yan, X. Zhang, Z. Lei, and S. Z. Li. Face detection by structural image and vision computing. 32(10):790–799, 2014.

[26] J. Vincent. Twitter’s photo-cropping algorithm prefers young, beautiful, and light-skinned faces. https://tinyurl.com/sxe7xmds, 2021. Online; accessed 27 August 2021.

[27] S. Yang, J. Liu, Z. L. Li, and Y. Qiao. Joint face detection and alignment using multitask cascaded convolutional networks. IEEE Signal Processing Letters, 23(10):1499–1503, 2016.

[28] S. Yang, J. Liu, Z. L. Li, and Y. Qiao. Joint face detection and alignment using multitask cascaded convolutional networks. IEEE Signal Processing Letters, 23(10):1499–1503, 2016.

[29] J. Vincent. Twitter’s photo-cropping algorithm prefers young, beautiful, and light-skinned faces. https://tinyurl.com/sxe7xmds, 2021. Online; accessed 27 August 2021.

[30] S. Yang, P. Luo, C.-C. Loy, and X. Tang. Wider face: A face detection benchmark. In IEEE conference on computer vision and pattern recognition, pages 5525–5533, 2016.

[31] K. Zhang, Z. Zhang, Z. Li, and Y. Qiao. Distance-iou as an evaluation metric is also required. In IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops, pages 0–1, 2020.