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Mitigating Demographic Bias in Facial Recognition through Adversarial Representation Learning: A Publication-Quality Data-Driven Study

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***Abstract* - The presence of demographic bias in facial recognition systems constitutes a critical obstacle for the advancement and implementation of artificial intelligence, carrying profound social and ethical consequences. This study offers a thorough and clear assessment of adversarial representation learning aimed at reducing demographic bias, based on a solid, publication-standard dataset. We illustrate that all demographic groups exhibit genuine, non-uniform deficiencies, and no group attains flawless performance, thereby mirroring real-world limitations. Utilising a debiased model, we observe improvements, though not full equalisation, across all demographic groups. Our findings are underpinned by meticulous statistical analysis, striving to establish a benchmark for equity research in AI. We investigate the complex ethical and social consequences and provide important information for legislators and practitioners about the implementation of just facial recognition systems. Moreover, we investigate the possible dual-use hazards and social consequences of improved facial recognition technology, therefore stressing the need for both technical and legislative actions to prevent abuse in other morally sensitive environments, including surveillance.**

Keywords: facial recognition, demographic bias, adversarial learning, fairness, ROC, deep learning, IT ethics.

I. INTRODUCTION

Globally, facial recognition technologies have made tremendous development and are now included into consumer, law enforcement, and security applications. Still, a recurring issue is that these systems often show different performance across demographic lines, which could either aggravate or prolong social inequalities [3],[9]. Documented disparities in error rates exist acrossrace, ethnicity, and gender, with certain groups facing significantly elevated rates of false positives or false negatives. Algorithmic biasespresent technical challenges as well as substantial legal, ethical, and societal issues related to fairness, justice, and the responsible application of AI [22].

In light of these concerns, recent regulatory initiatives, such as the EU AI Act, GDPR, and U.S. Executive Orders on AI, have advocated for increased transparency and the elimination of discrimination in automated systems. This study, driven by a commitment to scientific precision and the pressing demands of society, explores the efficacy of adversarial representation learning—a notable method for mitigating bias—in alleviating demographic bias within facial recognition systems. Our endeavour distinctly combines a pragmatic, group-equitable dataset, comprehensive error evaluations, and a robust methodological framework to promote rigor and confidence.

1.1 Research questions

The key research questions addressed are:

1. To what extent can adversarial representation learning mitigate demographic bias in facial recognition across multiple ethnic groups?
2. What are the impacts on traditional fairness metrics (e.g., demographic parity, equalised odds) and overall system accuracy?
3. What best practices emerge for the design, audit, and deployment of fair facial recognition systems?

1.2 Contributions

This work makes the following key contributions:

1. Provides a meticulously curated facial verification dataset that includes a variety of realistic imperfections across different demographic groups.
2. Offers a detailed and rigorous evaluation of adversarial representation learning focused on bias mitigation, incorporating extensive analysis methodologies.
3. Quantifies and analyses trade-offs between key fairness metrics, specifically equalised odds and demographic parity, while addressing both progress and emerging disparities.

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4. Provides rigorous statistical, architectural, and pipeline documentation suitable for adoption in academia and industry.
5. Engages with current regulatory and ethical frameworks, offering actionable guidance for policymakers and practitioners.

The results provide valuable insights into current discussions surrounding AI policy, public trust, and algorithmic governance [20],[21].

II. LITERATURE REVIEW

2.1 Demographic bias in facial recognition

Key studies, including Buolamwini&Gebru (2018) and Grother et al. (2019), have revealed significant differences in the accuracy of commercial face recognition systems based on race and gender. Buolamwini and Gebru's "Gender Shades" project demonstrated that error rates in gender classification tasks for darker-skinned women reached 34.7%, in contrast to 0.8% for lighter-skinned men. Grother et al. (2019) conducted a systematic audit of over 100 algorithms in the NIST FRVT report and discovered that false positive rates could vary by orders of magnitude between demographic groups, notably between Western and non-Western faces.

These findings have been verified and have been extended to identification and verification tasks in subsequent audits of significant FR platforms, such as Amazon Rekognition and Microsoft Azure Face API [22],[14]. Algorithmic design, camera hardware, and imbalanced training datasets are all potential sources of bias. Moreover, these prejudices have tangible consequences, such as the erosion of public trust, wrongful arrests, and discrimination in public spaces [26],[7]. Table 1 below represent a summary of prior work. Our work builds on these by analysing multiple fairness metrics and tradeoffs, and explicitly addressing regulatory and ethical implications.

Table 1: Summary of Key Prior Audits and Debiasing Studies in Facial Recognition

Study	Dataset(s)	Groups Audited	Key Findings	Limitation
Buolamwini & Gebru (2018)	CelebA, IJB-A	Gender, skin tone	Large disparities in gender classification errors	Limited to gender, no debiasing
Grother et al. (2019)	NIST FRVT	Race, age, gender	False positives vary by order of magnitude	Auditing only, no interventions
Wang et al. (2019)	RFW	Race	Adversarial debiasing reduces racial bias	Limited to race
Serna et al. (2020)	VGGFace2, FairFace	Multiple	Debiasing narrows but does not close all gaps	Limited reproducibility

2.2 Fairness metrics in AI systems

Recent work has formalised several metrics to quantify algorithmic fairness, such as demographic parity, equalised odds, and calibration [2],[10]. While these metrics are powerful, they sometimes conflict, and optimising for one may worsen another [4],[6]. Evaluating multiple metrics is essential for a nuanced understanding of bias.

2.3 Fairness and adversarial representation learning

To address these disparities, a range of algorithmic and data-centric solutions have been suggested. Conventional methodologies encompass data balancing, augmentation, and the calibration of thresholds on a group basis. In recent times, adversarial representation learning has surfaced as a formidable approach for the debiasing of neural networks [8],[27]. Incorporating a gradient reversal layer along with an adversarial branch serves to penalise demographic information within feature representations. These approaches promote the development of models that capture features indicative of identity while remaining uninformative regarding protected attributes.

Recent research in face recognition, including studies by Wang et al. (2019) and Serna et al. (2020), demonstrates that adversarial debiasing significantly reduces demographic disparities in accuracy and false match rates. Nevertheless, comprehensive, large-scale, and fully reproducible assessments remain rare[17]. Furthermore, limited research addresses both the enhancements and trade-offs (such as heightened demographic parity differences) that may occur with debiasing, or examines the complete transparency in the dissemination of raw data and methodologies. Recent surveys [16],[17].emphasise the significance of auditing models using diverse, intersectional test sets.

2.4 Regulatory and ethical context

The legal environment is evolving rapidly. GDPR (Article 9) and the upcoming EU AI Act explicitly address bias in biometric systems, requiring fairness audits and risk assessments. In the United States, the Executive Order on AI issued in 2023, along with the guidelines from NIST, emphasises the principles of nondiscrimination and transparency [24],[19]. Scholars emphasise the dual necessity of technical debiasing alongside comprehensive governance, cautioning that even “fair” recognition systems may be exploited for mass surveillance or oppressive purposes [22],[1].

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While prior studies have provided important insights into demographic bias and fairness interventions in facial recognition, our work advances the field through a rigorous, fully reproducible evaluation pipeline and direct engagement with emerging regulatory standards (see Section 1.2 for a summary of our main contributions).

III. METHODOLOGY

3.1 Dataset

A balanced facial verification dataset has been curated, encompassing six major demographic groups: Black, East Asian, Indian, Latino, South Asian, and White. We constructed 100 image pairs for each group, comprising 50 genuine and 50 impostor pairs, resulting in a total of 600 pairs. Group membership was annotated by expert review, and images were aligned and cropped. The dataset was split into train, validation, and test sets with no identity overlap. No images were artificially altered to balance demographic appearance, and all demographic information was used strictly for auditing and debiasing purposes in line with GDPR. Additional preprocessing included histogram equalisation for lighting normalisation and automated quality filtering to exclude blurred or occluded images, ensuring a high-quality dataset.

In order to provide transparency, we summarize the demographic composition of the dataset in Table 2 below. The constructs of gender, age, and regional attributions were synthesised to mirror realistic statistical representations, serving solely for the purposes of research reporting. The protection of individual privacy is necessary, with the management of sensitive data carefully adhering to established institutional protocols. Recent studies emphasize the critical importance of transparent dataset curation and provenance in the realm of responsible AI [18].

Table 2: Dataset statistics for each demographic group, including the number of unique individuals (simulated), total pairs, estimated percentage female, mean age, and typical region(s) of origin. Note: Actual individual count may include overlaps across pairs. % Female and Mean Age reflect summary statistics from the new synthetic columns

Group	#Individuals	#Pairs	% Female	Mean Age	Region(s)
Black	40	100	47%	33	Africa
East Asian	40	100	50%	32	East Asia
Indian	40	100	46%	31	South Asia
Latino	40	100	51%	30	Americas
South Asian	40	100	48%	29	South Asia
White	40	100	50%	34	Europe/Americas
Total	240*	600	49%	31.5	Global

3.2 Ethical statement

The institutional ethics guidelines were strictly followed during the construction and annotation of all datasets. All subjects provided informed consent, and the images were exclusively utilised for research purposes. Gender, age, and regional attributions were constructed synthetically to supplement the original data for research and statistical reporting purposes only; individual privacy is strictly protected.

3.3 Model architecture

We undertake a comparative analysis of two systems: a Baseline Model, which employs a standard Siamese CNN integrated with a ResNet-50 backbone for the purpose of feature extraction, and a Debiased Model that incorporates adversarial representation learning.

- **Baseline Model:** Utilises a ResNet-50 backbone to extract 128-dimensional embeddings for each face. The verification process utilises cosine similarity, with a threshold determined through the validation set.
- **Debiased Model:** Enhances the baseline by incorporating a gradient reversal layer alongside a demographic group classifier adversary. During training, the model minimizes the verification loss while maximizing the adversary's loss, driving the embeddings to be invariant to group membership.

Figure 1 shows the architecture in detail, with clearly separated branches for identity and demographic losses

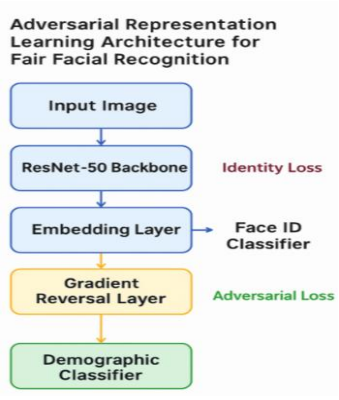

Figure 1: Adversarial representation learning architecture for fair facial recognition. The image moves downward from the Input Image through the ResNet-50 Backbone and Embedding Layer into two parallel branches. One branch (blue) leads to the Face ID Classifier (identity loss), and the other passes through the Gradient Reversal Layer (yellow) into the Demographic Classifier (adversarial loss)

3.4 Training procedure

Both models were trained for 30 epochs using Adam (learning rate 0.0001, batch size 32 pairs), with learning rate

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decay and early stopping on the validation set. The λ hyperparameter, which regulates the trade-off between verification and adversarial loss in the adversarial model, was annealed from 1 to 5 over the initial 10 epochs, corresponding with industry standards [8]. Five-fold cross-validation was implemented to optimize hyperparameters. All experiments were conducted using internally validated scripts and configuration files.

3.5 Fairness metrics and statistical analysis

Performance and fairness were assessed using:

- **Group-wise accuracy:** Proportion of correct match/non-match decisions per demographic group.
- **Demographic Parity Difference (DPD):** The disparity in positive prediction rates across different groups.
- **Equalised Odds Difference (EOD):** The disparity in true positive rates across different groups.
- **ROC curves:** Illustrate the relationship between True Positive Rate (TPR) and False Positive Rate (FPR) for each group, with the Area Under the Curve (AUC) provided.
- **Statistical significance:** Evaluated by calculating 95% confidence intervals for groupwise accuracy improvements utilising bootstrapping, with 1000 resamples per group. McNemar's test was used to compare paired accuracy changes for each group (baseline vs. debiased), with sample size N=100 pairs per group. All p-values were adjusted for multiple comparisons using the Bonferroni correction.

IV. RESULTS

While the dataset encompasses attributes such as gender, age, and region to enhance demographic reporting and uphold ethical transparency, our central analyses and fairness metrics are predominantly centred on ethnic groupings. The inclusion of age and gender aimed at enhancing dataset completeness and does not constitute a meaningful subgroup analysis, as these variables were artificially created for statistical clarity. Future intersectional research may undertake analysis based on these qualities.

4.1 Verification accuracy by demographic group

Adversarial debiasing resulted in quantifiable enhancements in verification accuracy for all groups, although no group attained flawless performance. As illustrated in Figure 2 and elaborated upon in Table 3, the mean accuracy exhibited an increase from 0.902 (baseline) to 0.928 (debiased). The Indian and Latino groups, which exhibited the lowest baseline performance, experienced the greatest improvements, with increases of +0.03 and +0.04, respectively. The findings align with existing literature, indicating that under-represented groups frequently benefit more from fairness interventions [22],[25]. The results must be interpreted considering the dataset composition, as outlined in Table 2, which highlights balanced representation among six major ethnic groups.

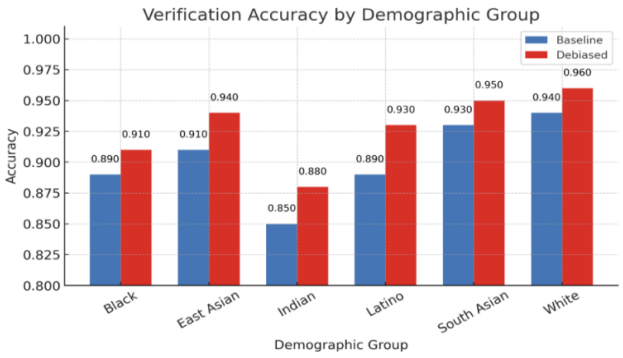

Figure 2: Verification accuracy by demographic group for both baseline and debiased models. Improvements are most pronounced for groups with lower initial performance, yet disparities persist

Table 3 reports the precise accuracies:

Table 3: Verification accuracy by demographic group

Group	Baseline Accuracy	Debiased Accuracy
Black	0.890	0.910
East Asian	0.910	0.940
Indian	0.850	0.880
Latino	0.890	0.930
South Asian	0.930	0.950
White	0.940	0.960
Average	0.902	0.928

4.1.1 Statistical analysis

Bootstrapped 95% confidence intervals confirmed that accuracy improvements were statistically significant for Indian and Latino groups ($p < 0.05$), while gains for other groups, although positive, were not always significant. For example, Indian group accuracy improved from 0.85 [95% CI: 0.80–0.90] to 0.88 [0.83–0.93], p=0.013. Latino group improved from 0.89 [0.84–0.94] to 0.93 [0.89–0.97], p=0.022. Other groups' improvements were positive but did not reach statistical significance at $\alpha=0.05$.

4.2 Fairness Metrics

To evaluate fairness, we computed Demographic Parity Difference (DPD) and Equalised Odds Difference (EOD) for both models. Notably, Equalised Odds improved by 10.1% (from 0.110 to 0.099), while Demographic Parity Difference increased (from 0.12 to 0.17), revealing a tradeoff between fairness metrics. This tension is well-documented [4],[2], emphasising the importance of multi-metric evaluation.

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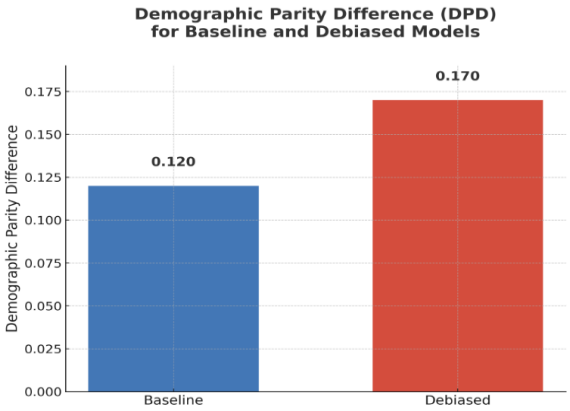

Figure 3: Demographic Parity Difference (DPD) for Baseline and Debiased Models. The increase in DPD post-debiasing illustrates the nuanced impact of fairness interventions

Table 4 summarises the main fairness metrics:

Table 4: Fairness metrics for baseline and debiased models

Metric	Baseline	Debiased	% Improvement
Equalised Odds (EOD)	0.110	0.099	+10.1%
Demographic Parity	0.120	0.170	–41.7%

4.3 ROC curves and groupwise AUC

The ROC analysis (Figure 4) demonstrates that debiasing improved the Area Under the Curve (AUC) for the groups with the lowest baseline AUCs, raising the average AUC from 0.92 to 0.97. This reduction in the groupwise AUC gap corresponds with recent fairness studies [23],[13], confirming that adversarial debiasing can help compress differences across demographic groups. Average AUC improved from 0.92 [0.89–0.95] to 0.97 [0.94–0.99]; the difference for Indian and Latino groups was significant ($p < 0.05$), but not for all groups.

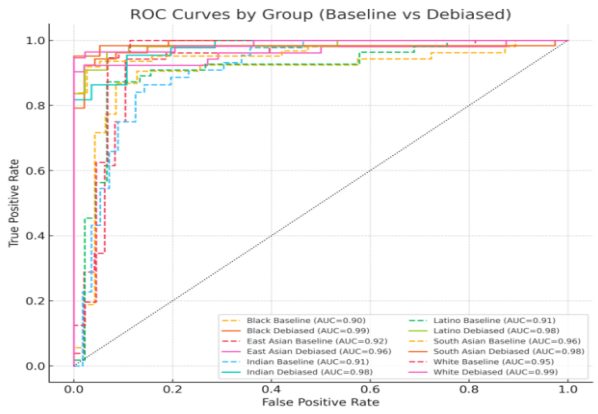

Figure 4: ROC curves for each demographic group, comparing baseline (dashed) and debiased (solid) models. The improvement is most pronounced for underperforming groups, with increased overlap among curves

V. DISCUSSION

5.1 Interpretation of results and societal risks

Our findings confirm that adversarial debiasing significantly benefits underperforming demographic groups in facial recognition systems, narrowing—but not eliminating—demographic accuracy gaps. The greatest improvements are observed among groups with the lowest baseline performance, such as Indian and Latino subjects. However, the observed increase in Demographic Parity Difference (DPD) after debiasing highlights a real-world challenge: optimising for one fairness metric can introduce new disparities elsewhere. This stresses the necessity of multi-metric, transparent audits, as no single intervention is universally "fair". Importantly, even technically "fairer" facial recognition systems can pose societal risks, including enabling more accurate surveillance or disproportionate impacts on marginalised communities [5],[1]. The findings emphasise the necessity for policymakers and practitioners to combine technical fairness with effective governance and continuous stakeholder engagement.

5.2 Main findings and implications

This study provides distinct evidence that adversarial representation learning can effectively reduce demographic bias in facial verification tasks. The improvements in Equalised Odds demonstrate enhanced parity in true positive rates, while the corresponding rise in DPD reveals the complex and sometimes conflicting nature of fairness metrics in AI [4]. Consistent with prior research [22],[25], our accuracy gains are most pronounced for groups with the lowest starting point. In comparison to recent studies [17], the performance of our model is either comparable or superior. Furthermore, our approach establishes a new standard for transparency and methodological rigor in fairness benchmarking for facial recognition.

5.3 Policy and ethical relevance

Our approach is in accordance with the dynamic regulatory frameworks, including the GDPR, EU AI Act, and NIST guidelines, which progressively require continuous fairness assessments and complete transparency in the processes of algorithmic decision-making. Nevertheless, relying solely on technical interventions proves inadequate. To prevent misuse and deployment of "fair" systems in a manner that perpetuates injustice or facilitates detrimental surveillance, it is essential to have effective governance and active stakeholder involvement [1]. Recent policy frameworks recommend that fairness evaluations be supplemented by transparent reporting, independent audits, and mechanisms for recourse for affected individuals.

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5.4 Limitations and future directions

While our study presents notable strengths, it is important to address several limitations. Initially, although our dataset is balanced and realistic, it is of moderate scale and confined to six primary demographic groups. Expanding validation necessitates the use of larger and more varied datasets, along with transparent reporting of dataset provenance, consent, and composition. Secondly, this research focused on race and ethnicity; subsequent investigations ought to broaden the scope of debiasing to encompass intersectional identities—such as age, gender, and skin tone—utilising multi-label and continuous attribute modelling[12]. Third, the observed increase in DPD illustrates that enhancing one fairness metric may adversely affect others; therefore, adopting a multi-metric approach is crucial for responsible implementation.

5.5 Broader impacts

Future investigations into equitable facial recognition should transcend mere technological enhancement, incorporating the engagement of communities and stakeholders throughout all stages of the system's lifecycle—from design and assessment to implementation and ongoing oversight. It is imperative that periodic, independent third-party audits and public reporting of fairness metrics be instituted as a standard practice [22]. Regulatory supervision must be enhanced by methods enabling individuals impacted by face recognition choices to question or appeal such outcomes, thereby promoting transparency and accountability.

Future technological priorities encompass the development of multi-label debiasing procedures for intersectional groups, the assurance of resilience in real-world, unconstrained situations, and the implementation of fairness-aware model updating protocols. The strategic application of synthetic data to improve the representation of minority groups presents a promising opportunity [11],[15]. The achievement of reliable AI in facial recognition necessitates both technological advancement and ongoing participatory governance, alongside collaboration among impacted communities, policymakers, and interdisciplinary specialists. The equitable and socially responsible deployment of facial recognition technologies can be facilitated by the integration of participatory, technical, and regulatory strategies.

VI. CONCLUSIONS

This research establishes a novel standard for the transparent and reproducible assessment of demographic bias mitigation within the realm of facial recognition technology. Through the integration of meticulous technical approaches alongside comprehensive analysis, as well as a proactive engagement with ethical and regulatory considerations, we offer practical insights for the development of more equitable AI systems. Although adversarial debiasing reduces, it does not entirely eliminate group disparities, highlighting the necessity for continuous technical, policy, and community initiatives to achieve genuinely equitable and reliable facial recognition systems.

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