
Addressing racial biasness in facial recognition

With algorithm engineering

NIST found rampant racial bias in majority of algorithms



NEWS

NIST Study Evaluates Effects of Race, Age, Sex on Face Recognition Software

Demographics study on face recognition algorithms could help improve future tools.

Amazon Rekognition

FALSE MATCHES



28 current members of Congress

Systemic factors leading to racial biasness in facial recognition

- Inadequate diversity inclusiveness in facial recognition training data
- Public benchmark tests LACK mechanisms to check for racial bias
 - Exception: 2019 launched Racial Faces in the Wild (RFW) Database
- The gold standard: NIST Facial Recognition Vendors Test
 - Standards-compliant photos (i.e. ID photos) only - lack of real-world tests and discounts camera-device's disproportionate impacts on dark skin individuals
 - Performance saturation: many algorithms scoring >95% accuracy even with racial bias
 - DOES NOT have comparable distribution of sample sizes of various ethnic demographics

The only public benchmark test measuring racial bias to date, Racial Faces in-the-Wild (RFW) circa 2019



[Submitted on 1 Dec 2018 (v1), last revised 27 Jul 2019 (this version, v2)]

Racial Faces in-the-Wild: Reducing Racial Bias by Information Maximization Adaptation Network

	African	East Asian	Caucasian	South Asian
Amazon	86.27%	84.87%	90.45%	87.20%
Microsoft	75.83%	79.67%	87.60%	82.83%
Face++	87.50%	92.47%	93.90%	88.55%

Accuracy scores of the major commercially available facial recognition algorithms on the RFW Database

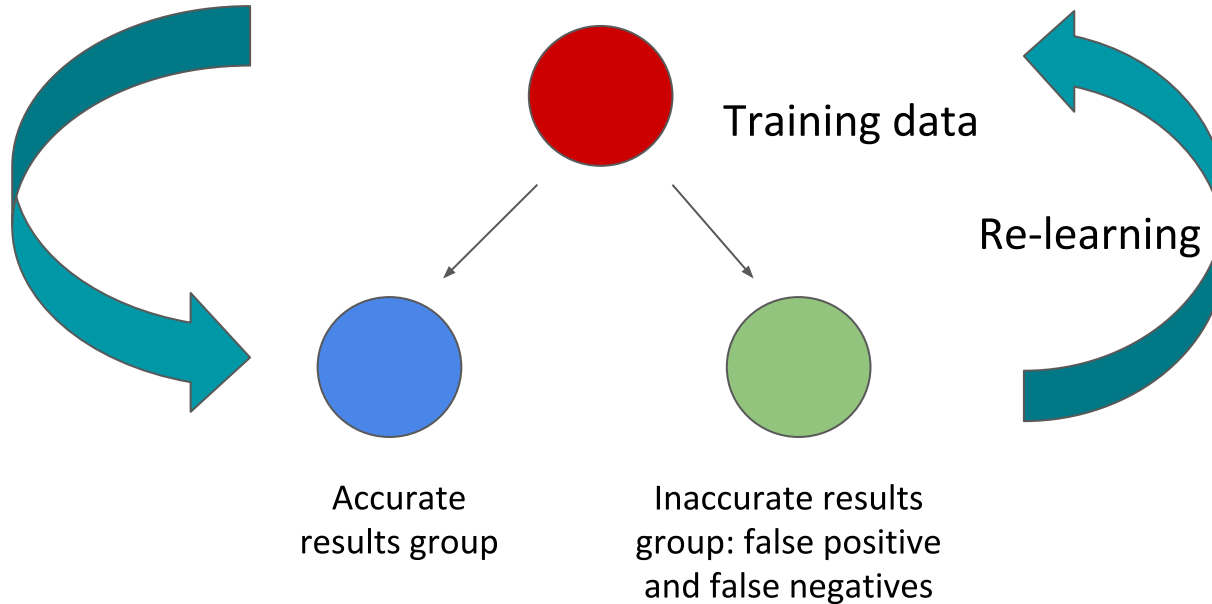
- Results show a significant reduction in performance saturation in comparison other public benchmarks, with most commercial algorithms scoring below 95% in accuracy
- Rampant racial bias is observed in Amazon, Microsoft and Face++ algorithms

So... how do we address racial bias in facial recognition?

Computer vision machine learning optimization

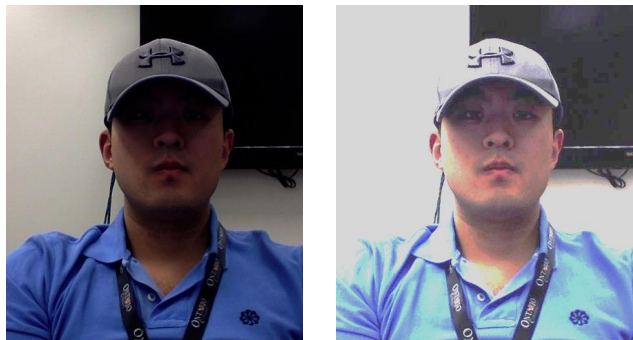
Not all artificial intelligence algorithms trained on the same set of data would behave similarly. Machine learning optimizations applying a variety of deep learning models, generative adversarial networks, neural network designs, and training methods can generate material impacts on AI.

Closing the gap on bias: triplet loss function



A concentrated approach to applying machine learning optimization on negative recognition results has helped us to close the gap on racial biasness in our facial recognition algorithm.

The paradox: colour consistency vs. image details in shadows



In the real world, face images are captured from a variety of cameras and lighting conditions, and facial algorithms are reliant on the accurate mapping of facial features in order to perform recognition tasks. This problem can be exacerbated by the racial biasness in camera designs.

Image lighting pre-processing using Multi-Scale Retinex Algorithm helps to maintain a fine balance in enhancing the local dynamics (i.e. revealing details in the shadows) and maintaining color consistency

Multiscale Retinex algorithm:

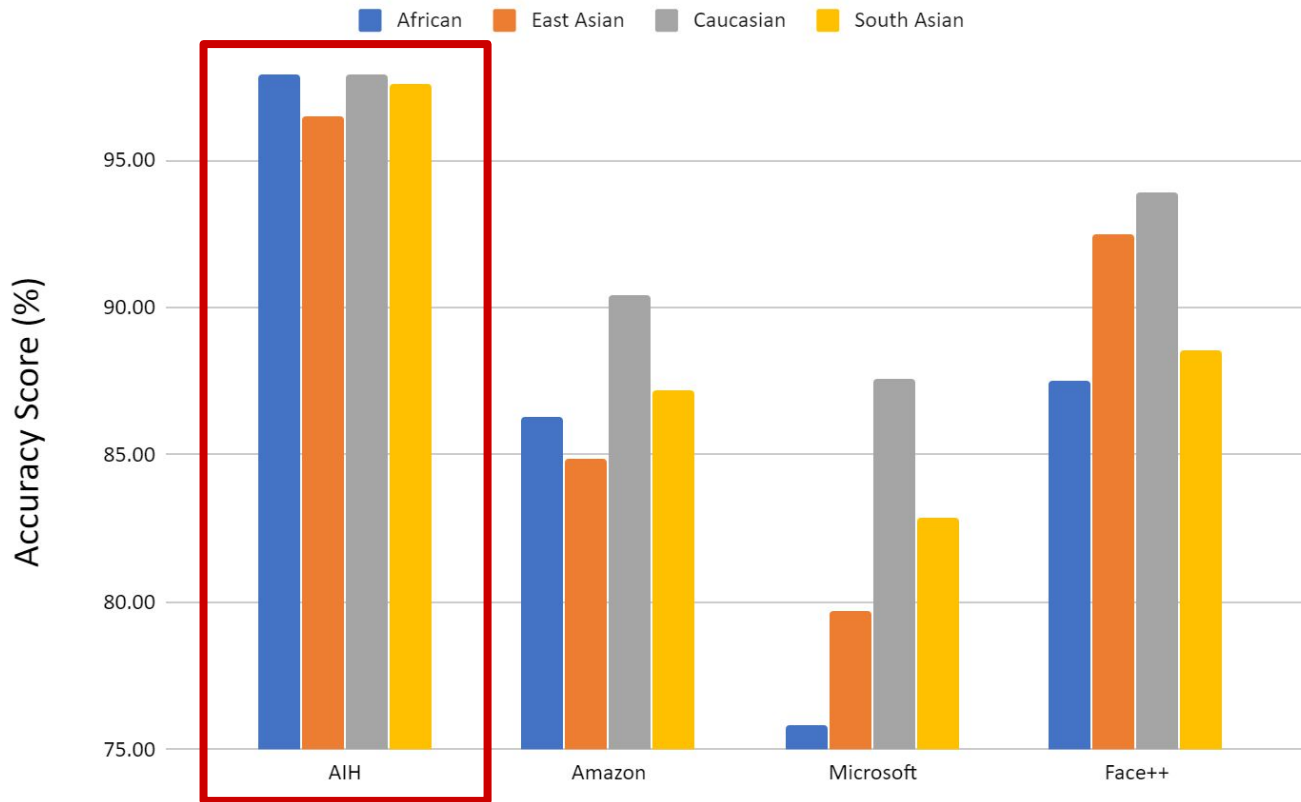
$$R_{MSR_i} = \sum_{n=1}^N w_n R_{n_i} = \sum_{n=1}^N w_n [\log I_i(x, y) - \log(F_n(x, y) * I_i(x, y))]$$

where N is the number of scales, w_n is the weight of each scale and $F_n(x, y) = C_n \exp[-(x^2 + y^2)/2\sigma_n^2]$

AIH FaceAlgo performance on RFW Database

	African	East Asian	Caucasian	South Asian
AIH	97.60%	96.07%	97.28%	97.25%
Amazon	86.27%	84.87%	90.45%	87.20%
Microsoft	75.83%	79.67%	87.60%	82.83%
Face++	87.50%	92.47%	93.90%	88.55%

AIH FaceAlgo performance on RFW Database



Conclusion

1. AIH FaceAlgo's overall accuracy performance across four ethnic groups scored consistently above **Amazon, Microsoft, and Face++**; and
2. AIH FaceAlgo exhibited minimal accuracy performance differentials amongst the four ethnic groups tested, and its accuracy score is the highest in the African group.



AIH Technology

Advancing ethical, responsible and inclusive application of AI technology