### Saving Face: Investigating the Ethical Concerns of Facial Recognition Auditing

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Apparently my manager's manager sent an email my direct reports saying she accepted my resignation. I hadn't resigned—I had asked for simple conditions first and said I would respond when I'm back from vacation. But I guess she decided for me:) that's the lawyer speak.

4:41 AM · Dec 3, 2020 · Twitter Web App

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### FACIAL PROCESSING TECHOLOGY

a broad term that encompasses a variety of tasks ranging from face detection, facial analysis, and face verification or identification.



### 80 Celebrities 20 for each group LM DM LF DF

Photo	Ethnicity	Colour	Gender	Age	Smile
		1 - 6	F/M	Photo Taken	Y/N

Table 1: Overall accuracy on designated facial analysis prediction tasks.

	Gender	Age	Name	Smile	Detection
Microsoft	99.94%	74.09%	98.69%	79.94%	93.56%
Amazon	99.75%	58.40%	87.25%	94.16%	99.25%
Clarifai	85.97%	55.24%	95.00%	56.19%	99.31%

Table 2: Difference in accuracy between the lighter (L) subgroup and darker (D) subgroup for each prediction task.

Task	Gender	Age	Name	Smile	Detection
Microsoft	0.13%	18.35%	1.41%	-0.48%	3.38%
Amazon	0.25%	16.83%	1.03%	-0.75%	0.25%
Clarifai	11.69%	1.00%	7.50%	0.12%	0.42%

Table 3: Difference in accuracy between the Male (M) subgroup and female (F) subgroup for each prediction task.

Task	Gender	Age	Name	Smile	Detection
Microsoft	0.13%	9.90%	1.23%	-4.45%	0.62%
Amazon	0.00%	12.28%	4.75%	-9.00%	0.50%
Clarifai	7.58%	10.26%	-1.01%	1.25%	-1.63%

Table 4: Difference in accuracy between the best and worst performing intersectional subgroups by prediction task. The subgroups are darker females (DF), darker males (DM), lighter females (LF) and lighter males (LM). Values in bold denote equal performance. For instance, 0.25% (DM/LM/LF - DF) signifies that the difference in accuracy between DM and DF, i.e. DM-DF, LM-DF and LF-DF are all 0.25%.

	Gender	Age	Name	Smile	Detection( $AP_{50}$ )
Microsoft	0.25% (DM/LM/LF - DF)	29.47% (LF-DF)	3.90% (LF-DF)	8.02% (LF-LM)	4.25% (LM-DM)
Amazon	0.50% (LF-DF)	29.10%(LM-DF)	6.71% (DM-DF)	9.75% (DF-LM)	0.75% (LM-DF/LF)
Clarifai	19.10% (LM-DF)	11.21% (LM-DF)	10.50% (LM-DF)	3.00% (LF-LM)	0.50% (LM/LF-DF)

## Design Considerations

# Consideration 1: Selecting Scope of Impact.

# Consideration 2: Auditing for Procedural Fairness.

Table 5: Breakdown of celebrity identities in commercial APIs by ethnicity.

	Asian	White	Hispanic	Black	Middle Eastern	Indian	Other/Mixed	Total
Microsoft API	7,838	15,536	10	8,816	995	1,316	7,167	41,678
	18.8%	37.3%	0.02%	21.1%	2.4%	3.2%	17.2%	100.0%

	Asian	winte	ruspanic	Diack	Middle Eastern	muian	Other/Mixeu	101
crosoft API	7,838	15,536	10	8,816	995	1,316	7,167	41,67
	18.8%	37.3%	0.02%	21.1%	2.4%	3.2%	17.2%	100.0

0.5%

1.9%

12.3%

100.0%

Microsoft API	7,838	15,536	10	8,816	995	1,316	7,167	41,678
	18.8%	37.3%	0.02%	21.1%	2.4%	3.2%	17.2%	100.0%
Clarifai API	172	4,861	0	534	31	125	800	6,523

8.2%

2.6%

74.5%

0.0%

## Ethical Tensions

#### ${\bf Table~6: Breakdown~of~IMDB-WIKI~data~examples~by~ethnicity}.$

	Asian	White	Hispanic	Black	Middle Eastern	Indian	Other/Mixed	Total
IMDB-WIKI-Eth	7,557	338,896	351	29,613	1,160	3,299	33,468	414,344
	1.8%	81.8%	0.1%	7.2%	0.3%	0.8%	8.1%	100.0%

#### Table 7: Breakdown of IMDB-WIKI data examples by gender.

		Male	Female	Unknown	Total
55.7% 43.4% 0.85% 100	IMDB-WIKI	230,912	179,900	3,532	414,344
		55.7%	43.4%	0.85%	100%

# Tension 2: Intersectionality and Group-Based Fairness.

## Tension 3: Transparency and Overexposure.



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