

Implications of Computer Vision Driven Assistive Technologies Towards Individuals with Visual Impairment

06/17/19

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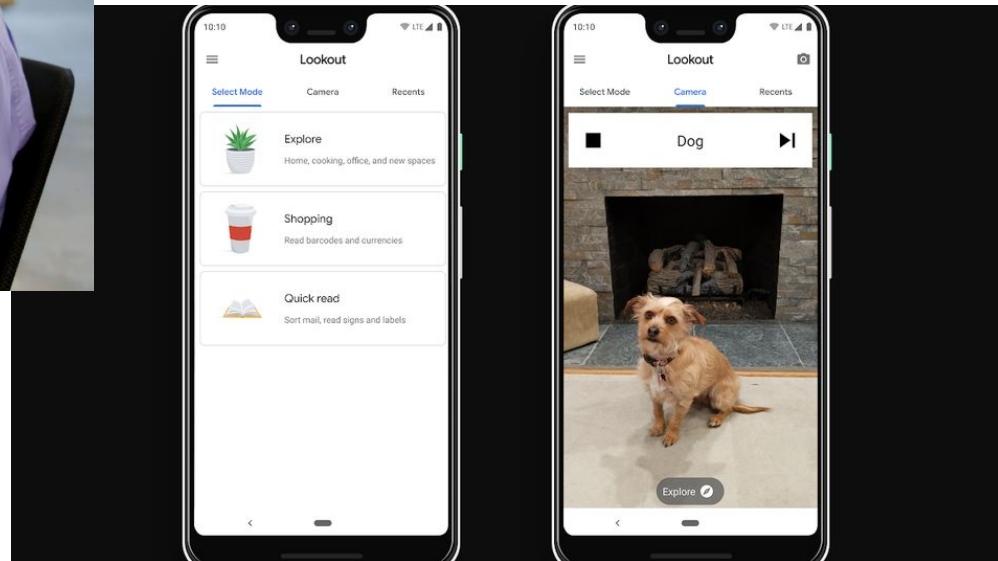
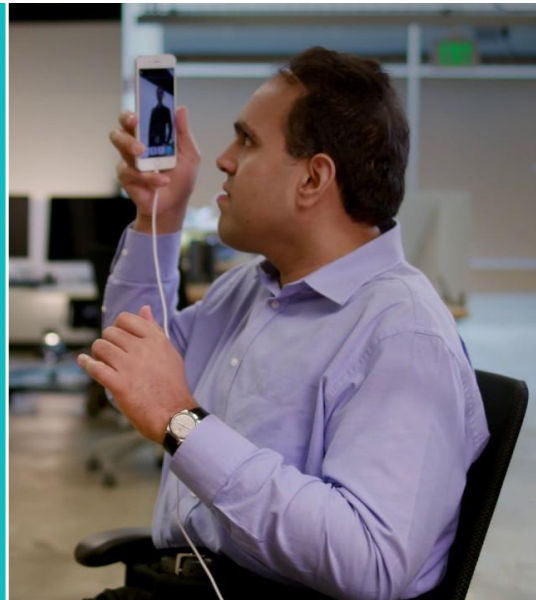
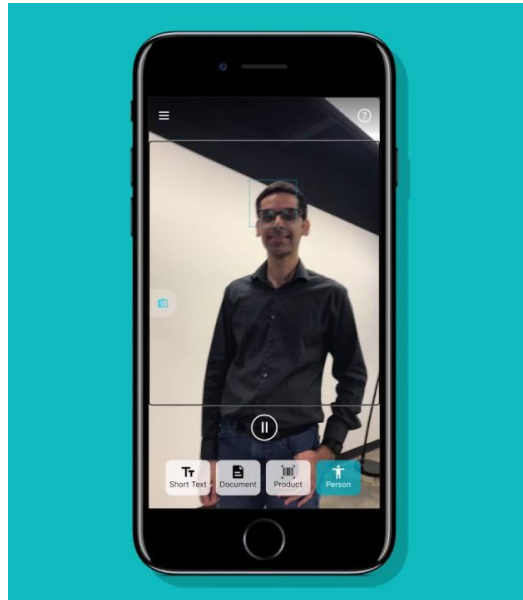
MASc in Systems Design Engineering
Software Engineering Intern at Lyft Level 5



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FACULTY OF ENGINEERING



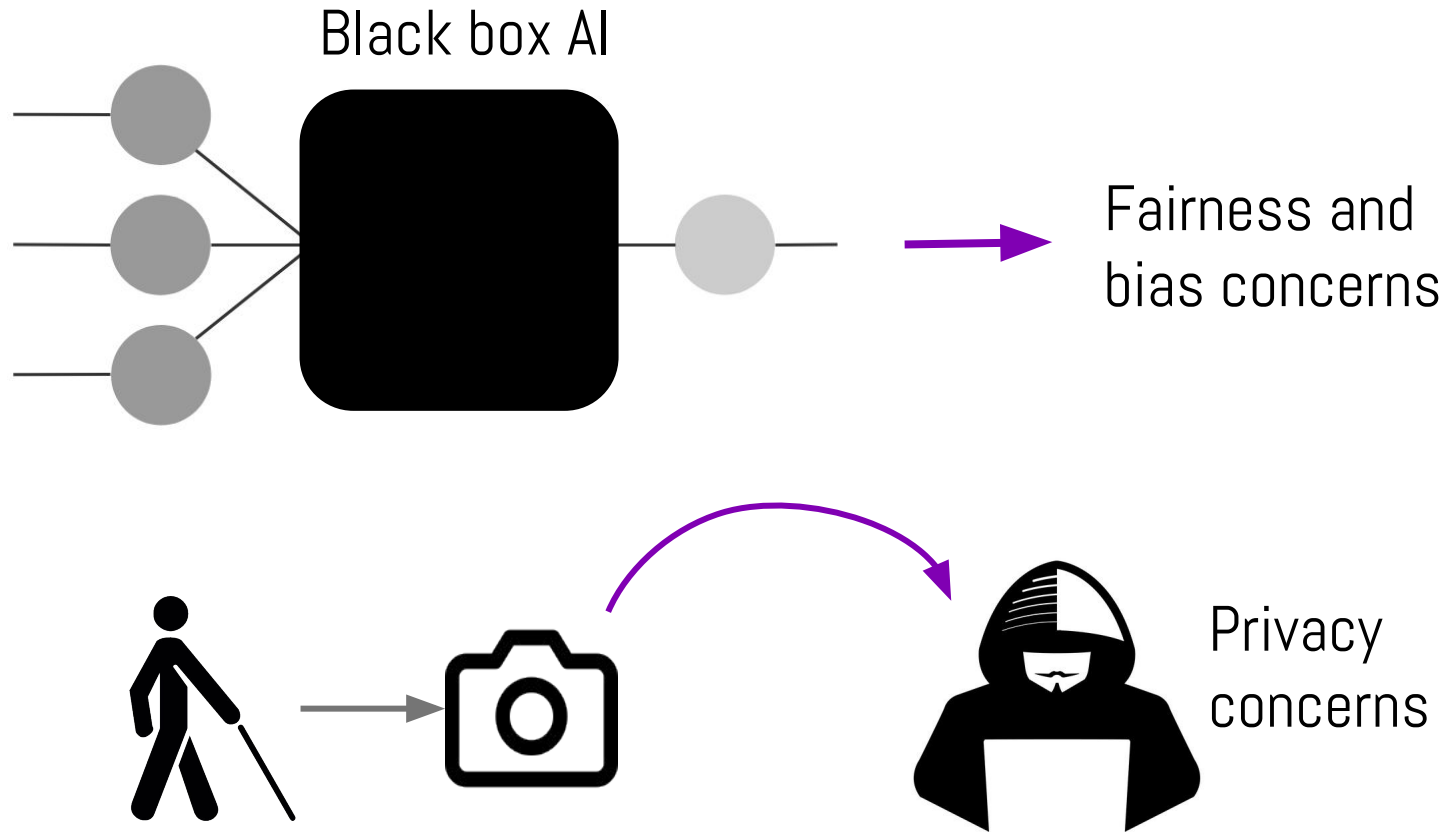
Motivation



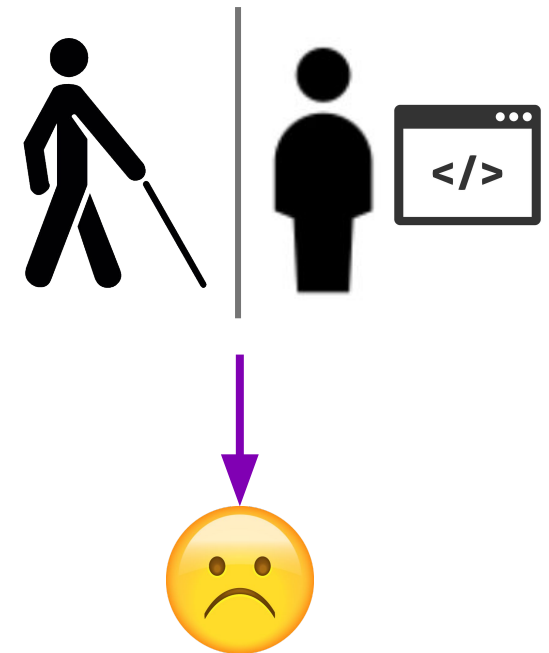
<https://www.perkinselearning.org/technology/blog/seeing-ai-ios-app-recognizing-people-objects-and-scenes>

<https://www.theverge.com/2019/3/13/18263426/google-lookout-ai-visually-impaired-blind-app-assistance>

Motivation



Exclusion during development process



Goal of the paper

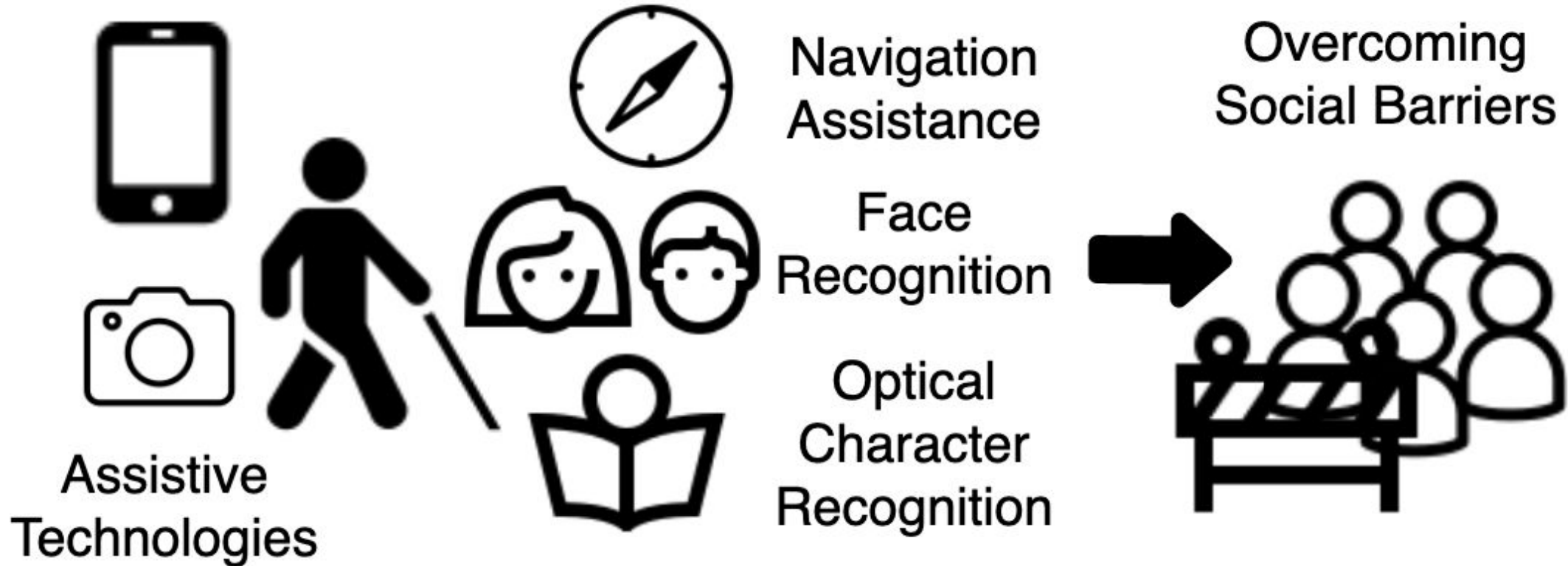
- Address the positive and negative aspects of using computer vision in assistive technologies for individuals with visual impairment
- Considerations for researchers while conducting computer vision research to reduce negative implications of AI-powered assistive technologies on the lives of individuals with visual impairment

Positive Implications

Face Recognition
and OCR

Navigation
Assistance

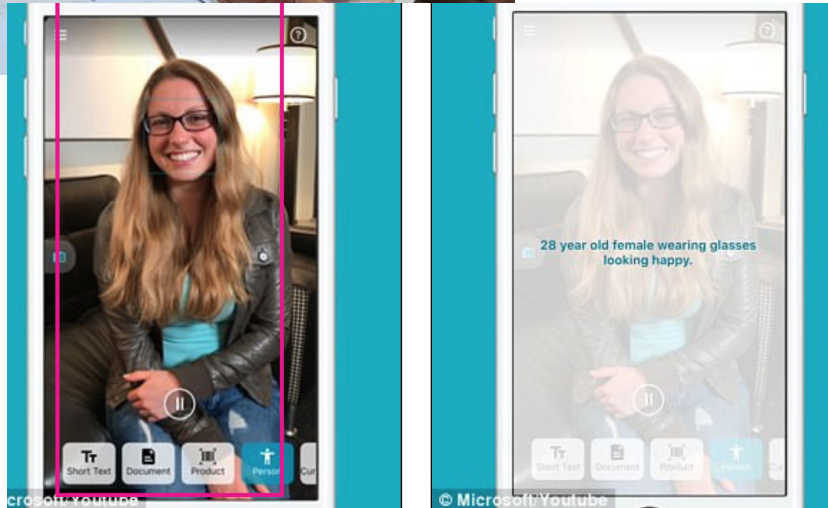
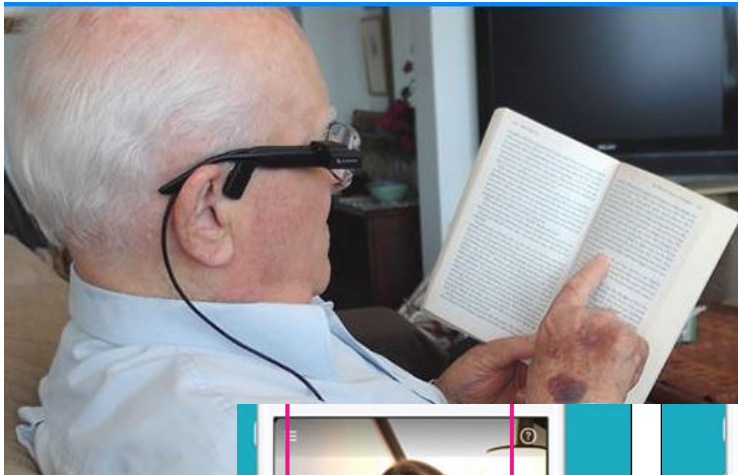
Overcoming
Social Barriers



Positive Implications

Face Recognition
and OCR

Navigation
Assistance



- Presence of smartphones + computer vision
 - means of communication → overcome social barriers
 - increase autonomy
 - and many more as computer vision advances

<http://cats.cuny.edu/orcam-my-eye-2-0/>

<https://www.abilitynet.org.uk/news-blogs/microsoft-seeing-ai-best-ever-app-blind-people-just-got-even-better>

Positive Implications

Face Recognition
and OCR

Navigation
Assistance



- Use of cameras + sensors to give directions
 - Localization for unknown indoor and outdoor environments
 - Helps to walk in a straight line
 - Helps to find rooms

<https://www.wsj.com/articles/hey-whats-with-the-white-cane-1476228132>

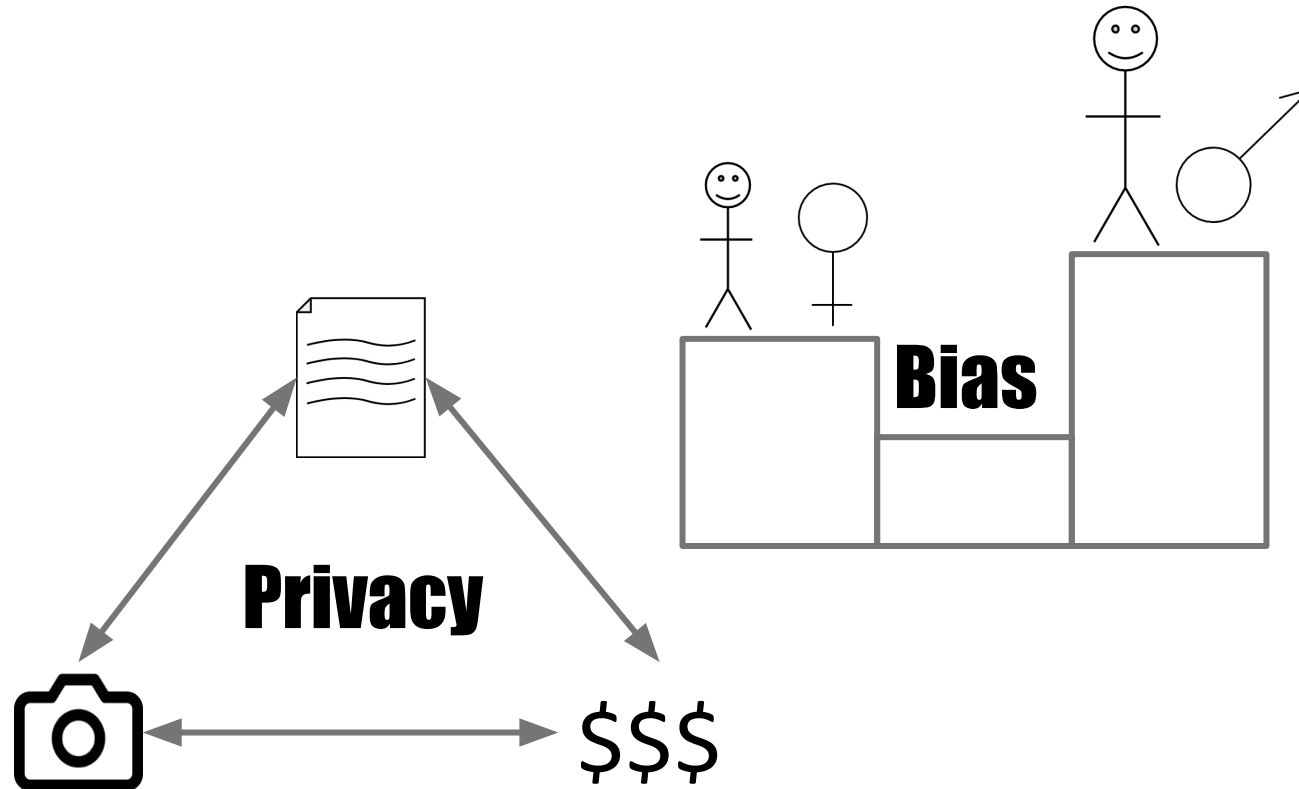
D. A. Ross. Implementing assistive technology on wearable computers. *IEEE Intelligent Systems*, 16(3):47–53, May 2001.
Y. Tian, X. Yang, C. Yi, and A. Ardit. Toward a computer vision-based wayfinding aid for blind persons to access unfamiliar indoor environments. *Machine vision and applications*, 24:521–535, 04 2013.

Negative Implications

Bias

Privacy

Exclusion



Exclusion in development process





Negative Implications

Bias

Privacy

Exclusion

Classifier	Metric	All	F	M	Darker	Lighter	DF	DM	LF	LM
MSFT	PPV(%)	93.7	89.3	97.4	87.1	99.3	79.2	94.0	98.3	100
	Error Rate(%)	6.3	10.7	2.6	12.9	0.7	20.8	6.0	1.7	0.0
	TPR (%)	93.7	96.5	91.7	87.1	99.3	92.1	83.7	100	98.7
	FPR (%)	6.3	8.3	3.5	12.9	0.7	16.3	7.9	1.3	0.0
Face++	PPV(%)	90.0	78.7	99.3	83.5	95.3	65.5	99.3	94.0	99.2
	Error Rate(%)	10.0	21.3	0.7	16.5	4.7	34.5	0.7	6.0	0.8
	TPR (%)	90.0	98.9	85.1	83.5	95.3	98.8	76.6	98.9	92.9
	FPR (%)	10.0	14.9	1.1	16.5	4.7	23.4	1.2	7.1	1.1
IBM	PPV(%)	87.9	79.7	94.4	77.6	96.8	65.3	88.0	92.9	99.7
	Error Rate(%)	12.1	20.3	5.6	22.4	3.2	34.7	12.0	7.1	0.3
	TPR (%)	87.9	92.1	85.2	77.6	96.8	82.3	74.8	99.6	94.8
	FPR (%)	12.1	14.8	7.9	22.4	3.2	25.2	17.7	5.20	0.4

Table 1: Overall Error on Pilot Parliaments Benchmark, August 2018 (%)

Company	All	Females	Males	Darker	Lighter	DF	DM	LF	LM
Target Corporations									
Face ++	1.6	2.5	0.9	2.6	0.7	4.1	1.3	1.0	0.5
MSFT	0.48	0.90	0.15	0.89	0.15	1.52	0.33	0.34	0.00
IBM	4.41	9.36	0.43	8.16	1.17	16.97	0.63	2.37	0.26
Non-Target Corporations									
Amazon	8.66	18.73	0.57	15.11	3.08	31.37	1.26	7.12	0.00
Kairos	6.60	14.10	0.60	11.10	2.80	22.50	1.30	6.40	0.00

J. Buolamwini and T. Gebru. Gender shades: Intersectional accuracy disparities in commercial gender classification. In S. A. Friedler and C. Wilson, editors, *Proceedings of the 1st Conference on FAT*, volume 81 of *PMLR*, pages 77–91, 23–24 Feb 2018.

I. D. Raji and J. Buolamwini. Actionable auditing: Investigating the impact of publicly naming biased performance results of commercial ai products. In *Conference on AIES*, 2019.

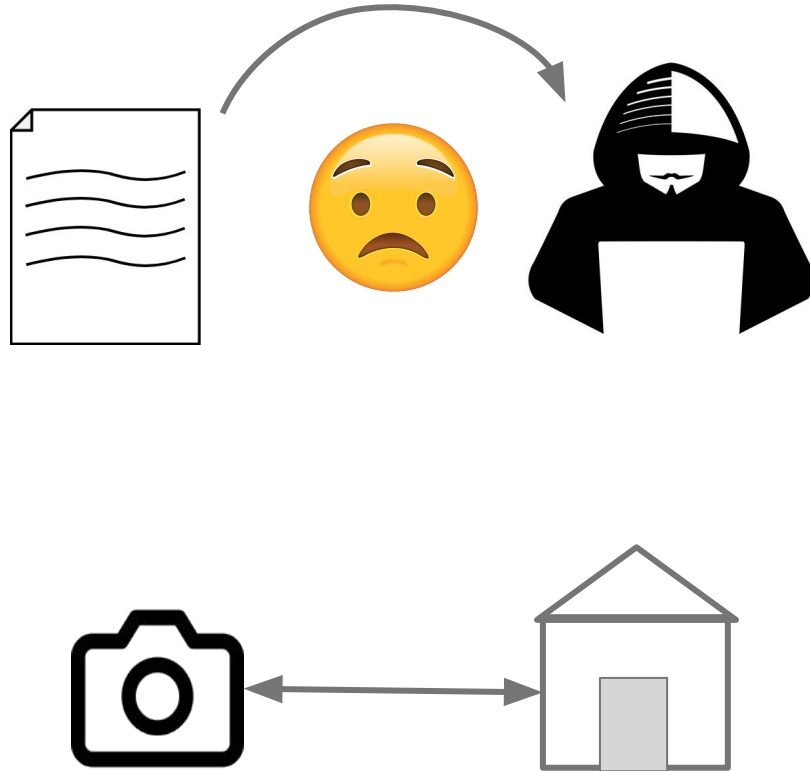
- Low error rates in facial recognition has led to commercialization of models
- Studies have shown consistent bias in areas of gender, race and age
→ Adversely impacting already marginalized groups
- Commercialization before evaluating biases and potential impacts on protected groups raises a concern

Negative Implications

Bias

Privacy

Exclusion



- Privacy concerns because of the amount of personal data stored
 - home monitoring: older adults are willing to share with family and doctors if data is useful, but concerned about exploitation and misuse of their personal data
- Found cameras obtrusive
 - trade-off privacy lost if prevent transfer to long-term care

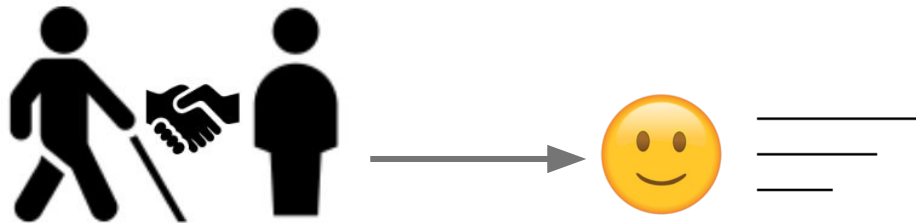
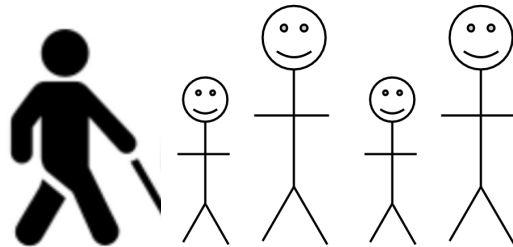
<https://www.vectorstock.com/royalty-free-vector/creative-hidden-hacker-logo-vector-22540040>

Negative Implications

Bias

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Exclusion



Inclusion of
End Users

- Good design, usability and accessibility can be poorly evaluated
- Need to consider user's lifestyle and aspirations
 - age and level of adaptation to condition
 - no matter the age, all individuals expressed inclusion by peers and appearing ordinary
 - more accustomed individuals prefer to be more independent

→ Inclusion of end users

Design Considerations

Bias Mitigation

Disability
Discrimination

Inclusion of
End Users

Diverse Skill
Set

Diverse
Skill Set



Bias
Mitigation



Inclusion of
End Users



Disability
Discrimination

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What-If Tool

Home

Introduction

Features

Demos

About

References

What If...

you could inspect a machine learning model,
with minimal coding required?

OPEN PROJECT

AI Fairness 360

The AI Fairness 360 toolkit (AIF360) is an open source software toolkit that can help detect and remove bias in machine learning models

<https://developer.ibm.com/open/projects/ai-fairness-360/>
<https://pair-code.github.io/what-if-tool/>

Mitigating Bias in Gender, Age and Ethnicity Classification: A Multi-task Convolution Neural Network Approach

Abhijit Das^(✉), Antitza Dantcheva, and Francois Bremond

CAPUCHIN: CAUSAL DATABASE REPAIR FOR ALGORITHMIC FAIRNESS

A PREPRINT

Babak Salimi

Luke Rodriguez

Bill Howe

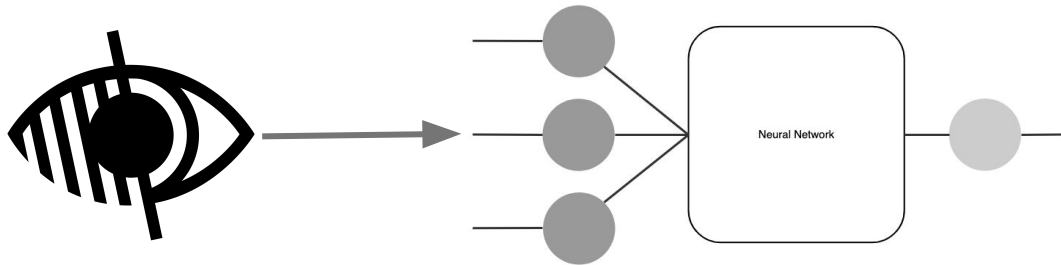
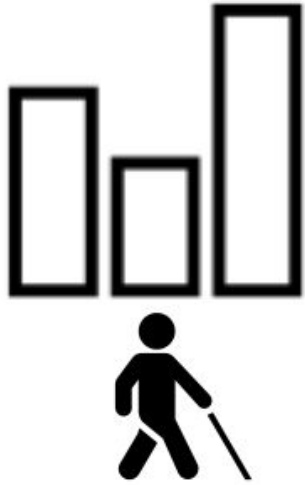
Design Considerations

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Set



- Ways to mitigate disability bias have not been explored → potential for under-representation of individuals with visual impairment or other forms of disability
- Different forms and degrees
 - Difficult for machine learning to generalize

<https://achievementcenteroftexas.org/special-needs/vision-impairment-center/>

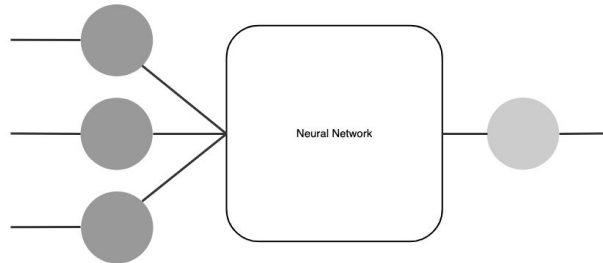
Design Considerations

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User's needs and requirements



A task specific training set and appropriate
model architecture



Computer vision based devices to be
perceived as useful

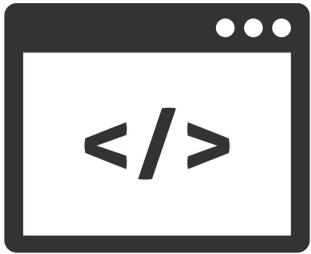
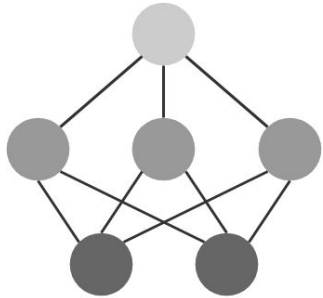
Design Considerations

Bias Mitigation

Disability
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End Users

Diverse Skill
Set



- Need a team with a diverse skill set to address both positive and negative implications
- Ex:
 - Researchers → bias
 - Developers → data security
 - Designers → user's needs and goals

<https://www.vectorstock.com/royalty-free-vector/custom-coding-icon-vector-13512550>

<https://www.onlinewebfonts.com/icon/190597>

Discussion

- Conclusion:
 - Identified positive and negative implications of computer vision based assistive technologies towards the visually impaired
 - Identified ways to mitigate negative implications
- Future work:
 - Consider possible implications of trained models and adopt ways to mitigate these implications
 - Take the same views towards other marginalized groups

Thank you for listening!

Questions?

