FIRE: THE FIRST-YEAR INNOVATION & RESEARCH EXPERIENCE
COMPUTING & SOCIETY

AI Bias in Facial Recognition Systems

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Research Questions

Quantitative:
How does the accuracy of facial recognition technology differ when identifying individuals from various races and age groups in a controlled environment?

Qualitative:
How do developers of facial recognition systems perceive and address the challenges related to bias within these systems?

Background

Usage of Facial Recognition Technology:
- Commonly utilized in security, law enforcement, and personal devices.

Issues with Bias:
- Exhibits biases across race, gender, and age caused by imbalanced datasets and design choices.

Impact of Bias:
- Results in higher error rates for certain demographic groups and raises significant fairness concerns.

Focus of the Study:
- Examines disparities in facial recognition accuracy across demographics.
- Explores developer efforts to mitigate these biases.

Methodology

Research Approach
- Mixed-methods study examining facial recognition bias
- Combined statistical analysis with developer interviews

Quantitative Analysis
- Measured accuracy rates across demographics
- Applied statistical testing to validate findings

Qualitative Insights
- Conducted interviews with AI developers
- Explored bias mitigation strategies:
  - Technical approaches
  - Organizational methods

Integrated Findings
- Comprehensive analysis of demographic disparities including current mitigation approaches
- Combined statistical evidence with practical solutions

Results/Findings

"When we look at people who are both older and from minority groups, the system often fails them the most. It's as if the algorithm can't handle the complexity of their identity."

Bias in Development: Facial recognition systems show bias from imbalanced datasets that misrepresent demographic groups, reflecting societal inequities.

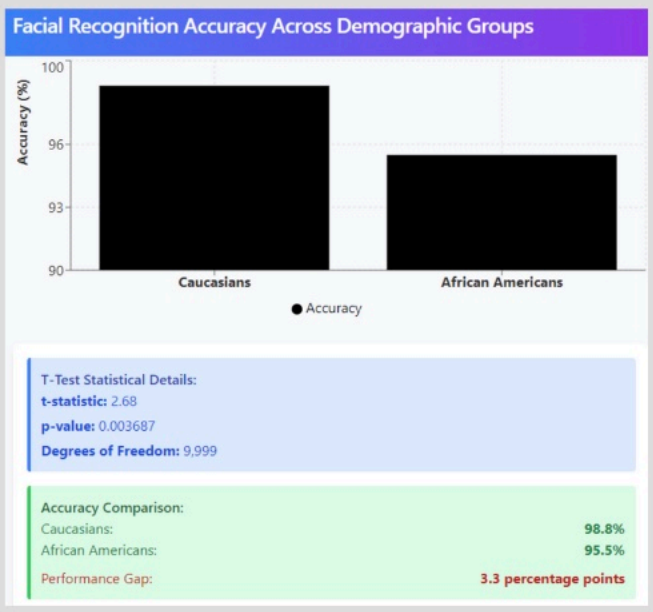
Accuracy vs. Fairness: Developers struggle between maximizing accuracy and ensuring demographic fairness, with market pressures often favoring the former.

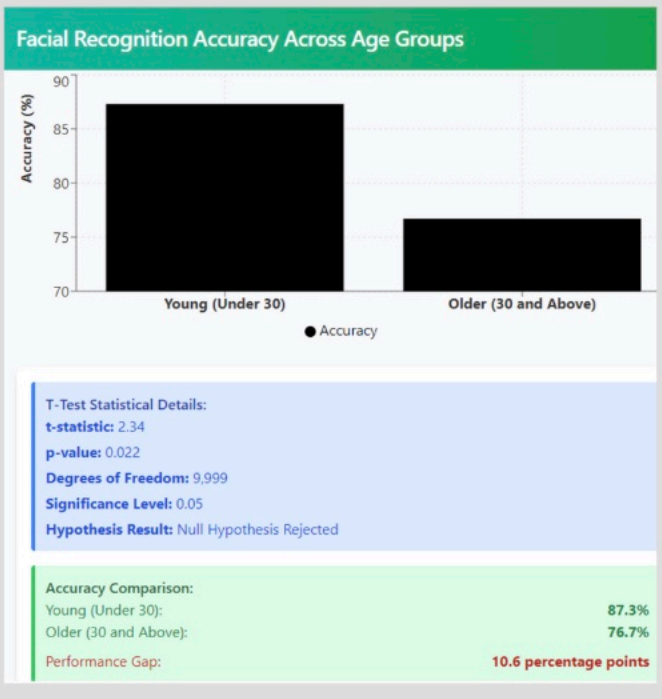
Barriers to Mitigation: Main obstacles include lack of team diversity, limited fairness research funding, and weak equity regulations.

Strategies: Key solutions include community partnerships, fairness metrics implementation, and external auditing for accountability.

Intersectional Impact: Systems perform poorest for those with multiple marginalized identities, requiring comprehensive fairness approaches.

"Without diverse voices on our teams, we end up building systems that work well for the people designing them but fail for everyone else. It's not just a technical issue—it's about who gets to make the decisions and whose experiences are considered."





Discussion

Quantitative Data:
- **Statistical bias confirmed ($p<0.05$): racial bias $p=0.00387$, age bias $p=0.022$**
- **Accuracy disparities: Caucasian vs African-American recognition rates differ significantly; younger subjects 87.3% vs older 76.7%**
- **Results confirm inconsistent performance across demographics**

Qualitative Data:
- **Unbalanced training data identified as primary bias source**
- **Improving accuracy for one group often decreased it for others**
- **Key barriers: lack of team diversity and limited fairness research funding**
- **Multiple marginalized identities faced highest misidentification risk**

References

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