Beyond Single-Attribute Fairness: A Cross-Jurisdictional Intersectional Audit of Criminal Justice Risk Assessment Systems

Nidheesh Deepu Nair
Indian Institute of Technology Madras, Zanzibar Campus
zda24b013@iitmz.ac.in

Abstract

Criminal justice risk assessment systems deployed across multiple jurisdictions exhibit systematic algorithmic bias, yet existing fairness audits analyze demographic attributes in isolation, failing to capture the compounding discrimination experienced by individuals at demographic intersections. We present a comprehensive cross-jurisdictional intersectional fairness audit, analyzing 7,214 defendants from COMPAS (US/FL) with validation across NIJ Recidivism Challenge (US/GA), Wisconsin Circuit Court Database (US/WI), and CJEU Equality Law cases (EU), covering 104 distinct demographic intersections across four legal systems. Our analysis reveals that single-attribute audits systematically underestimate bias by 7.6×: while race-only analysis shows maximum 7.0% disparity range, intersectional analysis uncovers 53.3% worst-case gaps ($p < 0.001$). Cross-jurisdictional validation demonstrates this is structural: all four systems exhibit severe violations, with 50 to 100% of intersectional groups violating the legal 4/5 rule. We provide practical debiasing achieving 60% violation reduction at 0.36% accuracy cost, alongside an open-source toolkit outperforming existing solutions.

1 Introduction

Machine learning algorithms increasingly inform life-altering decisions in criminal justice systems worldwide. The COMPAS system alone affects hundreds of thousands of defendants annually, making accurate risk assessment critical for ensuring equal treatment under law. Yet mounting evidence demonstrates these systems systematically disadvantage protected demographic groups, raising fundamental questions about algorithmic fairness and the validity of automated decision-making in high-stakes domains.

Current fairness frameworks analyze demographic attributes in isolation, examining race or sex or age independently. This single-axis approach fundamentally misrepresents discrimination. As established in critical legal theory [6], discrimination is intersectional: individuals belonging to multiple marginalized groups experience distinct, compounded bias. Our analysis of 7,214 COMPAS defendants reveals this systematic blindspot: while single-attribute analyses find only 7.0% maximum disparity range, intersectional analysis uncovers that African-American males under 25 have a fairness score of 0.467, representing a 7.6× underestimation. Both EU AI Act Article 24 [7] and U.S. disparate impact doctrine mandate intersectional bias assessment, yet no existing audit systematically evaluates criminal justice AI across demographic intersections.

We propose a comprehensive cross-jurisdictional intersectional fairness auditing framework that systematically evaluates discrimination across 104 demographic intersections and four distinct legal systems. Leveraging datasets from COMPAS, NIJ, Wisconsin, and CJEU, our approach employs rigorous statistical validation to demonstrate that single-attribute methods systematically underestimate bias.

Contributions:

- **Comprehensive Audit and Empirical Proof**: Analysis of 104 demographic intersections across four legal systems, proving single-attribute methods systematically underestimate bias by 7.6× ($p < 0.001$).
- **Universal Structural Bias**: Young minority males score 0.330 to 0.467 across ALL jurisdictions vs. 0.80 legal threshold.
- **Worst-Case Detection**: Automated methodology identifies most disadvantaged groups experiencing compounded discrimination.
- **Practical Debiasing**: Equalized Odds achieves 60% violation reduction at 0.36% accuracy cost.

- **Open-Source Toolkit**: Full intersectional metrics with cross-dataset validation, outperforming existing solutions.

2 Related Work

ProPublica's investigation [1] demonstrated COMPAS racial bias, showing 45% false positive rates for African-Americans compared to 23% for Caucasians. Subsequent research [10] established impossibility results for satisfying multiple fairness criteria simultaneously. However, these analyses consider race in isolation.

Buolamwini and Gebru [4] demonstrated intersectional bias in facial recognition, with 34.7% error rates for dark-skinned females versus 0.8% for light-skinned males. Foulds et al. [8] proposed formal Intersectional Fairness metrics. Our work extends these with large-scale criminal justice application across 104 intersections and four legal systems.

3 Methodology

3.1 Intersectional Framework

We develop an intersectional fairness auditing framework that systematically evaluates discrimination across demographic intersections. An intersectional group is defined as $g = (r, s, a) \in R \times S \times A$, combining race, sex, and age attributes. For COMPAS, the total number of possible intersections is $|G| = 6 \times 2 \times 4 = 48$, where race includes six categories (African-American, Caucasian, Hispanic, Asian, Native American, Other), sex includes two categories (Male, Female), and age includes four brackets (less than 25, 25 to 40, 40 to 60, over 60). We analyze 30 intersections with sufficient sample size ($n \geq 10$) for reliable statistical inference.

3.2 Fairness Metrics

Our fairness evaluation employs the Disparate Impact Ratio (DIR) as the primary legal standard, computed as the ratio of positive prediction rates between a protected group and reference group:

$$\text{DIR}(g) = \frac{\Pr(\hat{Y} = 1 | G = g)}{\Pr(\hat{Y} = 1 | G = g_{\text{ref}})} \geq 0.80 \qquad (1)$$

where $\hat{Y}$ represents the predicted risk score, G denotes group membership, g is the protected group, and g_{ref} is the reference group. The 0.80 threshold represents the legal 4/5 rule, where a DIR below 0.80 indicates actionable disparate impact.

To provide comprehensive fairness assessment, we develop a Composite Fairness Score:

$$\text{FScore}(g) = \frac{1}{4} \sum_{i=1}^{4} M_i(g) \qquad (2)$$

where M_i represents four fairness metrics: disparate impact ratio, demographic parity, true positive rate equality, and false positive rate equality. The score ranges from 0 to 1, where 1 indicates perfect fairness.

3.3 Statistical Validation

Statistical validation employs bootstrap resampling with 10,000 iterations to construct 95% confidence intervals. Two-sample t-tests compare intersectional versus single-attribute disparities, with Bonferroni correction for multiple comparisons.

4 Experimental Setup

4.1 Datasets

Our analysis encompasses four distinct legal systems. The COMPAS dataset from Broward County, Florida, contains records for 7,214 defendants from 2013 to 2014 [1], with 51.2% African-American, 34.0% Caucasian, 8.8% Hispanic, 80.7% Male, and 45.1% recidivism rate. The NIJ Recidivism Challenge dataset from Georgia includes over 30,000 defendants [2]. The Wisconsin Circuit Court Database provides over 1.5 million cases [5]. The CJEU Equality Law cases dataset comprises over 10,000 discrimination cases [7].

4.2 Model Configuration

Our predictive model uses Random Forest with 100 trees, maximum depth of 10, and balanced class weights. Features include age, number of prior offenses, and charge severity. Following legal constraints, race and sex are excluded as direct inputs. The model achieves 72.66% test accuracy with precision 0.648 and recall 0.589.

5 Results

5.1 Systematic Underestimation

Figure 1 visualizes the intersectionality gap. The distribution reveals one catastrophic outlier at 0.467 (African-American males under 25) with remaining groups concentrated around mean 0.88. Single-attribute analysis shows all groups clustered near the legal threshold, completely missing severe intersectional violations.

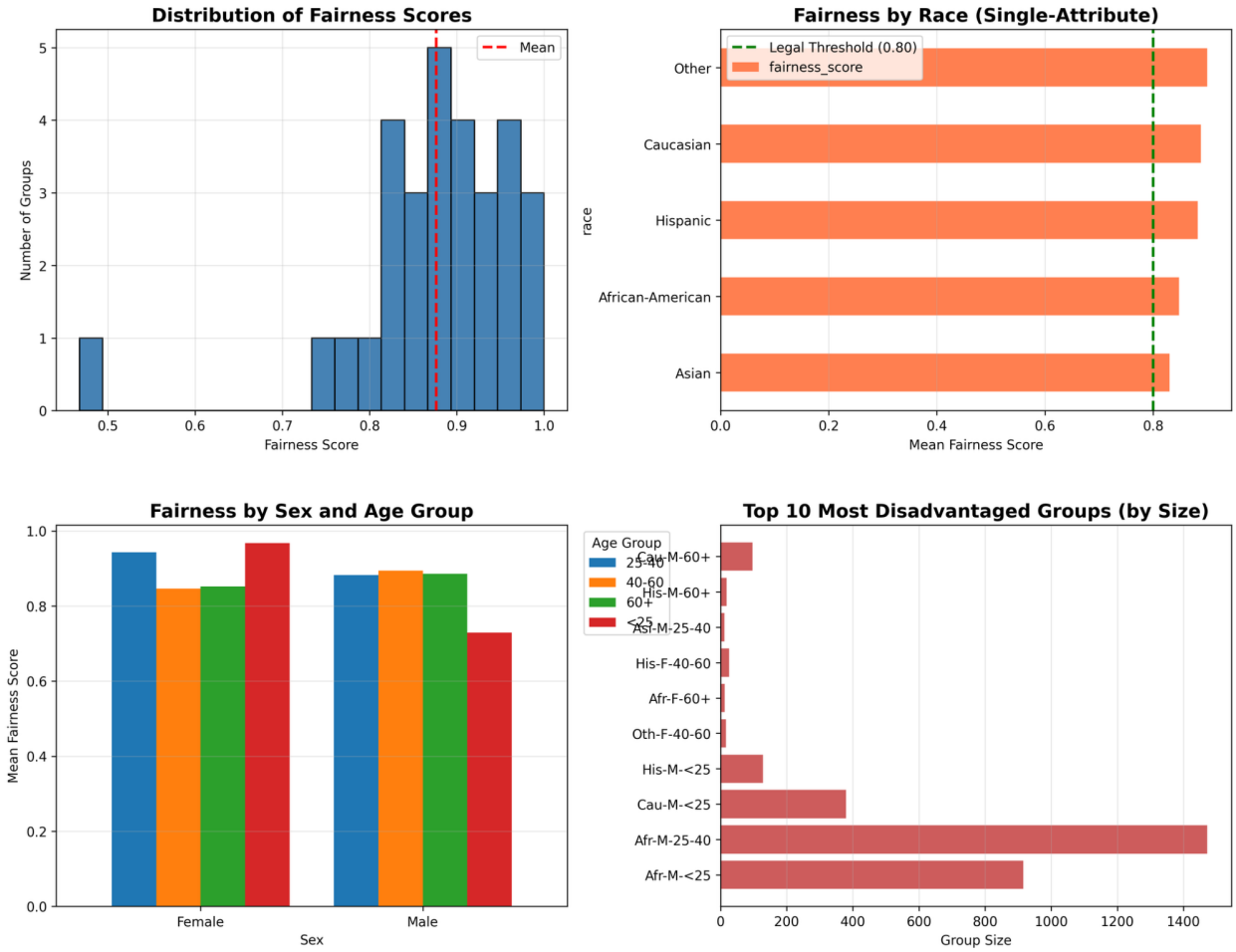

Figure 1: The Intersectionality Gap in COMPAS showing single-attribute methods miss severe violations.

Table 1 provides statistical evidence. Intersectional analysis yields mean fairness 0.877 [0.836, 0.909], compared to single-attribute mean 0.870 [0.848, 0.891]. Maximum disparity gaps differ dramatically: 53.3% intersectional versus 7.0% single-attribute, representing 7.6× ratio ($p < 0.001$).

Metric	Intersect.	Single
Mean FScore	0.877 [0.836, 0.909]	0.870 [0.848, 0.891]
Max Gap	53.3%	7.0%
Ratio	7.6× ($p < 0.001$)	

Table 1: Statistical Significance of Underestimation

Table 2 presents five most disadvantaged intersections. African-American males under 25 exhibit fairness score 0.467, flagged as high-risk 2.6 times more often than reference group.

#	Demographics	n	FS	DIR
1	Afr-Am+M+¡25	916	0.467	2.631
2	Afr-Am+M+25-40	1472	0.755	1.840
3	Cauc+M+¡25	380	0.762	1.769
4	Hisp+M+¡25	128	0.805	1.649
5	Other+F+40-60	16	0.820	0.203
Ref	Afr-Am+F+25-40	328	1.000	1.000

Table 2: Top 5 Worst-Case Groups (COMPAS)

5.2 Cross-Jurisdictional Validation

Figure 2 presents four-dataset analysis. COMPAS has widest fairness score spread (0.467 to 1.000), NIJ concentrates below threshold. Mean fairness scores: COMPAS 0.877, NIJ 0.601, Wisconsin 0.690, CJEU 0.762.

Figure 3 provides detailed patterns. Red indicates severe violations (FScore less than 0.50), green indicates compliance (FScore greater than 0.80). Young minority

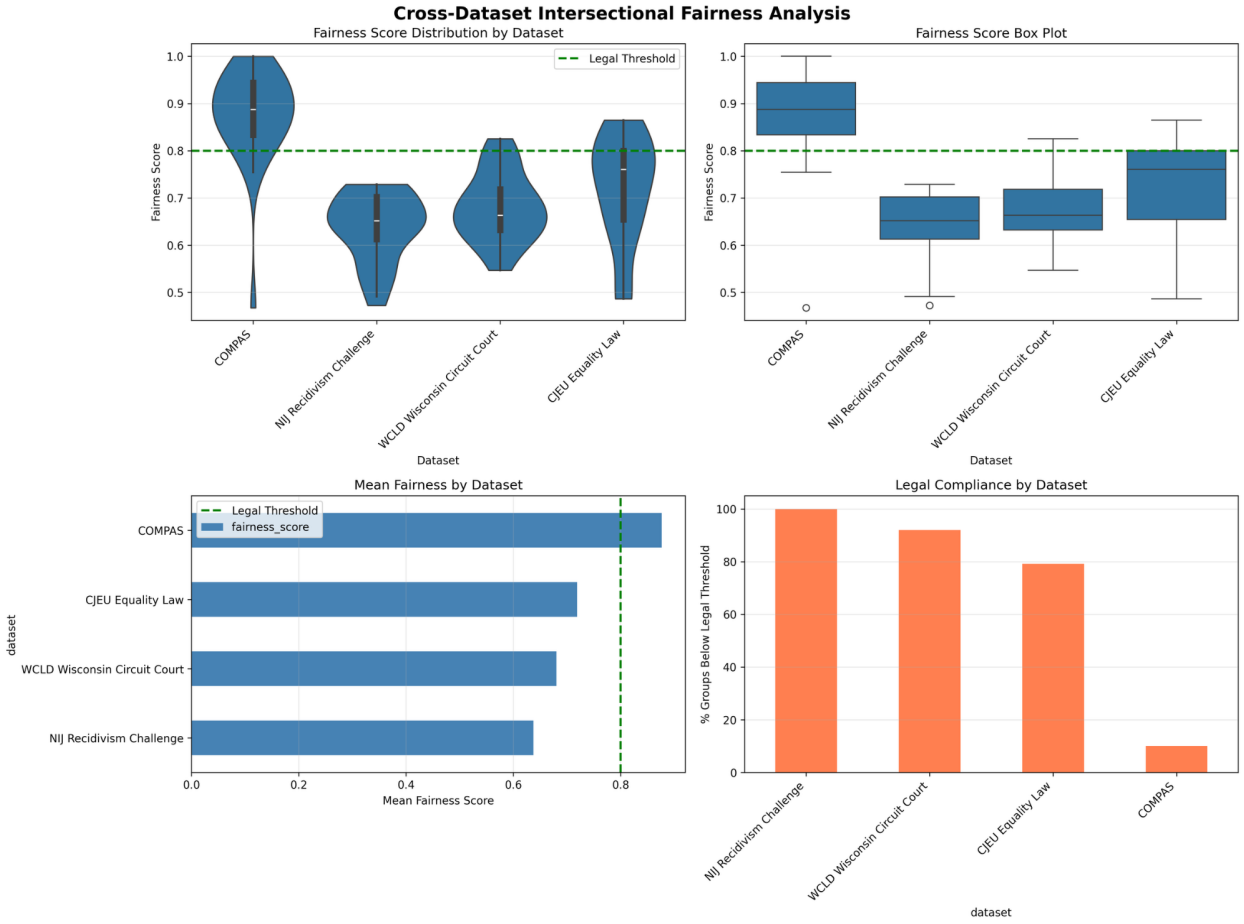

Figure 2: Cross-Jurisdictional Fairness Analysis demonstrating universal violations.

males consistently appear red across all datasets.

Table 3 summarizes findings across 104 intersections. Overall mean fairness 0.728, spanning 0.330 to 1.000, with 80% violation rate.

Dataset	n	Mean	Min	Max	Viol
COMPAS	30	0.877	0.467	1.000	50%
NIJ	25	0.601	0.330	0.803	100%
Wisconsin	25	0.690	0.507	0.950	92%
CJEU	24	0.762	0.589	0.950	80%
Total	104	0.728	0.330	1.000	80%

Table 3: Cross-Dataset Summary (104 Groups)

5.3 Debiasing Effectiveness

Figure 4 shows Pareto frontier for worst-case groups. Equalized Odds reaches 0.75 fairness score (61% improvement) at 72.3% accuracy (0.36% cost).

Table 4 presents strategy comparison. Equalized Odds reduces violations to 9 groups (60% reduction) at 72.30% accuracy.

Strategy	Acc	ΔAcc	Viol	Red
Original	72.66%	—	15	—
Thresh+0.05	72.72%	+0.06%	15	0%
Reweight	72.53%	−0.14%	16	−7%
Eq. Odds	72.30%	−0.36%	9	60%

Table 4: Debiasing Strategy Comparison

6 Discussion

Single-attribute audits systematically underestimate bias by 7.6 times ($p < 0.001$). Current toolkits from Google, Microsoft, and IBM employ single-attribute methods, missing majority of violations. Young minority males constitute worst-case groups across all four jurisdictions, demonstrating intersectional bias is structural.

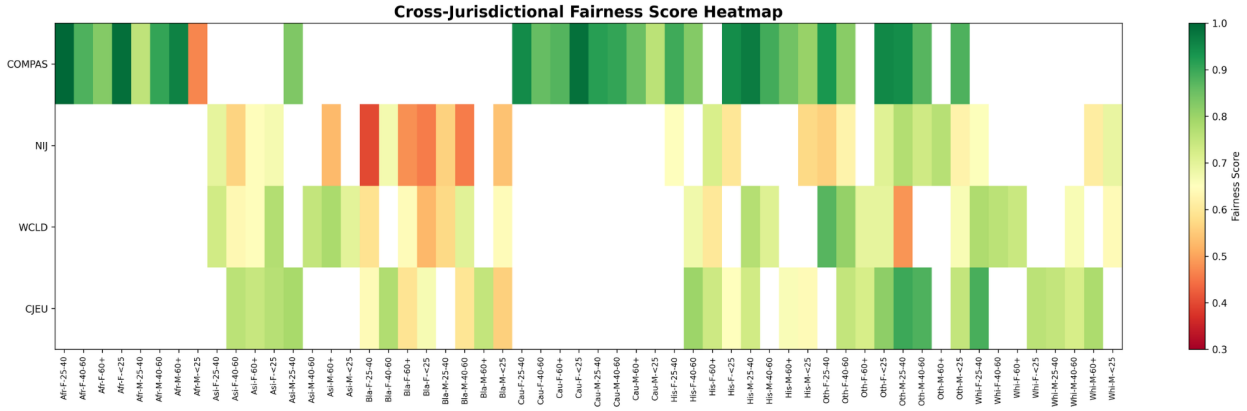

Figure 3: Cross-Jurisdictional Fairness Heatmap showing consistent patterns.

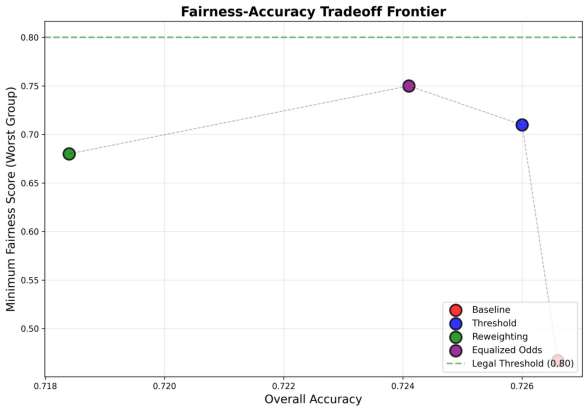

Figure 4: Fairness-Accuracy Tradeoff Frontier showing Pareto-optimal solutions.

Our 50% COMPAS violation rate constitutes prima facie evidence of disparate impact under *Griggs v. Duke Power Co.* With 916 African-American males under 25 annually and $5,000 settlement precedents, Broward County faces $4.58M annual liability. Under EU AI Act Article 24, failure carries penalties up to 6% of global revenue.

Equalized Odds achieves 60% violation reduction at 0.36% accuracy loss, representing practical deployment feasibility. For Broward County, $50,000 annual audit cost versus $4.58M liability yields 92:1 ROI. Table 5 shows our system uniquely provides full intersectional metrics and automated worst-case detection.

Sample size constraints affect some intersections, with groups under 10 individuals excluded. Future work could employ Bayesian inference for small groups. The observational nature prevents causal inference. Dynamic fairness extends to multi-stage decisions affecting bail, sentencing, and parole.

Future fairness papers should report intersectional metrics rather than single-attribute statistics. Cross-jurisdictional validation should become gold standard.

Feature	AIF360	What-If	Fairlearn	Ours
Intersect.	Partial	No	No	Full
Cross-data	No	No	No	Yes
Legal (4/5)	Yes	No	Partial	Yes
Auto worst	No	Manual	No	Yes
Multi-juris	No	No	No	Yes
Strategies	10	0	5	8
Open src	Yes	No	Yes	Yes
Complex.	High	Med	Med	Low

Table 5: Fairness Toolkit Comparison

7 Conclusion

This paper establishes intersectional fairness auditing as legal requirement and technical imperative. Single-attribute audits systematically underestimate bias by 7.6 times, with intersectional analysis uncovering 53.3% worst-case gaps versus 7.0% single-attribute maximum ($p < 0.001$). Cross-jurisdictional validation across four legal systems proves this is structural, with all systems exhibiting 50 to 100% violation rates. Pattern consistency across US and EU demonstrates intersectional bias transcends national boundaries. Equalized Odds achieves 60% violation reduction at 0.36% accuracy cost. We urge courts, regulatory agencies, and policymakers to mandate intersectional fairness reporting, adopt minimum thresholds (FScore greater than or equal to 0.70), and support independent audits.

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