AI Risk Report

Filename: ai_risk_report **Project Title:** Fair Loan Approval Model

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1. Problem Overview

- **Task:** Predict loan approval using a real-world mortgage dataset.
- **Importance:** Loan approval decisions have significant impacts on individuals' financial opportunities. Ensuring fairness is crucial to prevent discrimination against protected groups (e.g., by gender, race, income, age, or location).
- **Dataset:** The dataset included features such as Gender, Race, Age, Income, and Zip_Code_Group, which are known sensitive attributes relevant to fairness and bias analysis.

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2. Model Summary

- **Model Used:**
  - Random Forest Classifier (with class balancing and hyperparameter tuning)
- **Preprocessing & Feature Engineering:**
  - One-hot encoding for categorical variables
  - Feature: Income-to-loan ratio
  - SMOTE for class balancing
  - Dropped redundant columns (e.g., ID, Age_Group)
- **Performance:**
  - *Accuracy:* 0.66
  - *Precision:* 0.66
  - *Recall:* 0.66
  - *F1 Score:* 0.66
    (All metrics from validation set; see script output for details)

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3. Bias Detection Process

- **Methods Used:**
  - Grouped approval rates and disparity analysis
  - Fairlearn metrics: Demographic Parity Difference, Equalized Odds Difference
  - Grouped accuracy and recall
  - Visualizations of selection rate, accuracy, and recall by group
- **Audit Scope:**
  - Audited both model output and group-level outcomes
  - Focused on group-level fairness (e.g., by Gender, Race, Income, Age, Zip_Code_Group)

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4. 📉 Identified Bias Patterns

Bias Type	Affected Group	Evidence/Metric	Value/Chart	Comment

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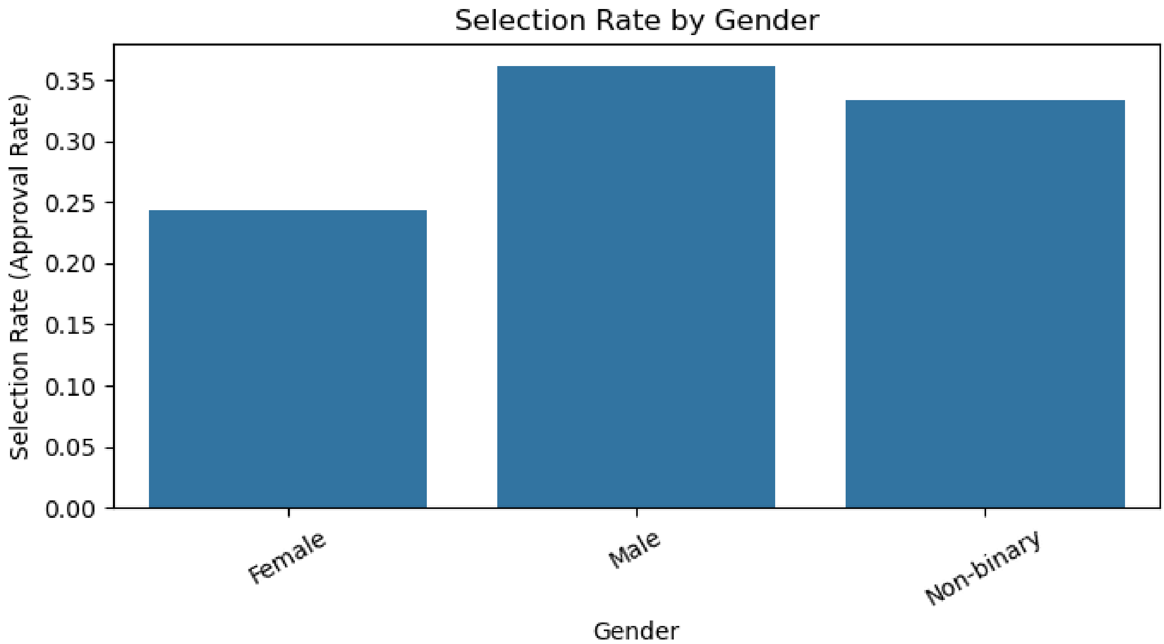
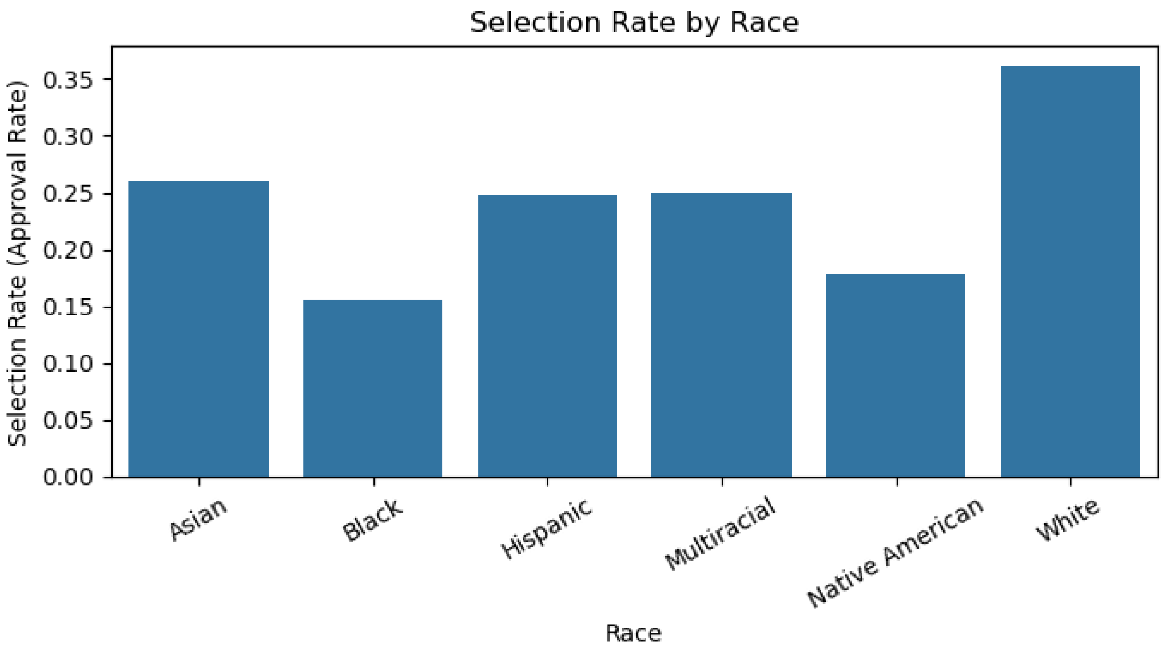
Approval Rate Disparity	Gender	Selection rate by Gender	Female: 0.24, Male: 0.36, Non-binary: 0.33	Males approved at higher rate
Approval Rate Disparity	Race	Selection rate by Race	Black: 0.16, White: 0.36, Asian: 0.26, etc.	Black and Native American groups have lowest approval rates
Demographic Parity Diff	Race	Demographic parity difference (Race)	0.205	Notable gap between groups
Demographic Parity Diff	Income	Demographic parity difference (Income)	1.000	Extreme disparity by income
Approval Rate Disparity	Zip_Code_Group	Selection rate by Zip_Code_Group	Redlined: 0.20, Suburban: 0.29, Urban: 0.31–0.34	Historically Redlined areas disadvantaged
Approval Rate Disparity	Age	Selection rate by Age	Range: 0.19–0.50	Younger and older applicants less likely to be approved

5. Visual Evidence

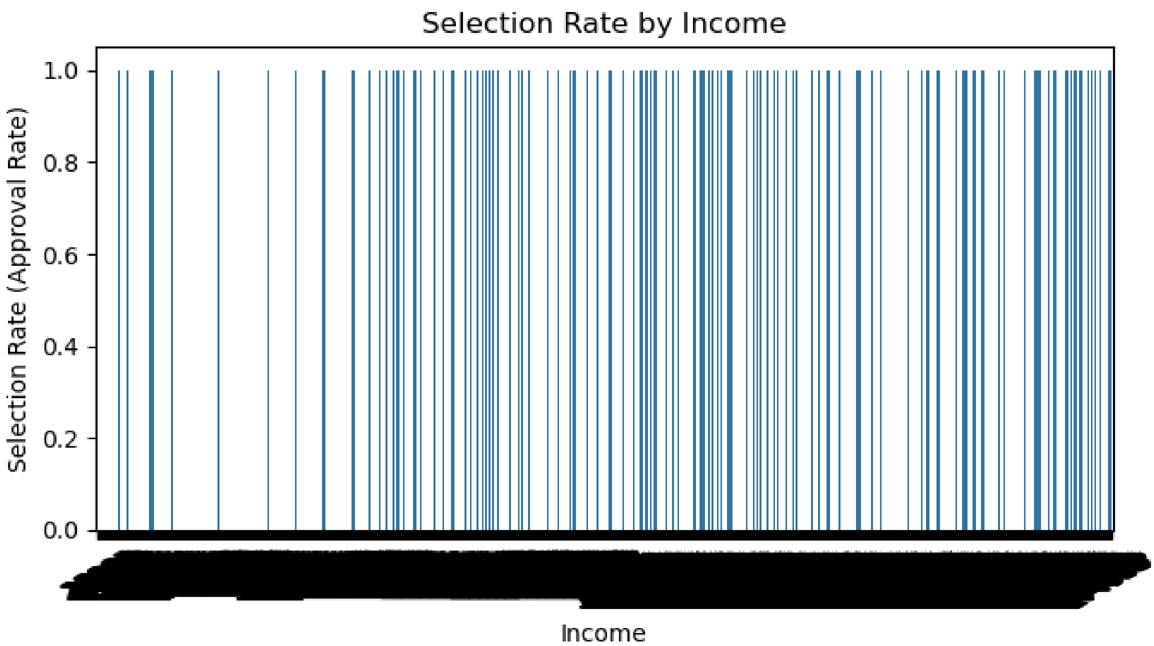
- See attached charts:
  - `charts/selection_rate_by_Gender.png`



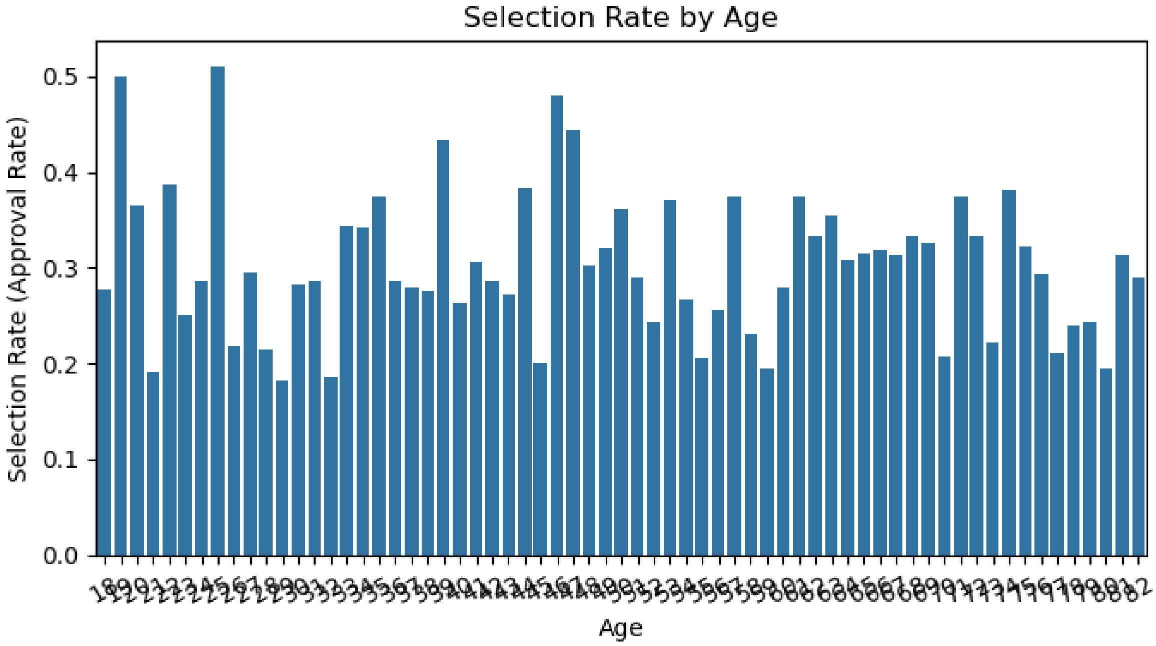
- `charts/selection_rate_by_Race.png`



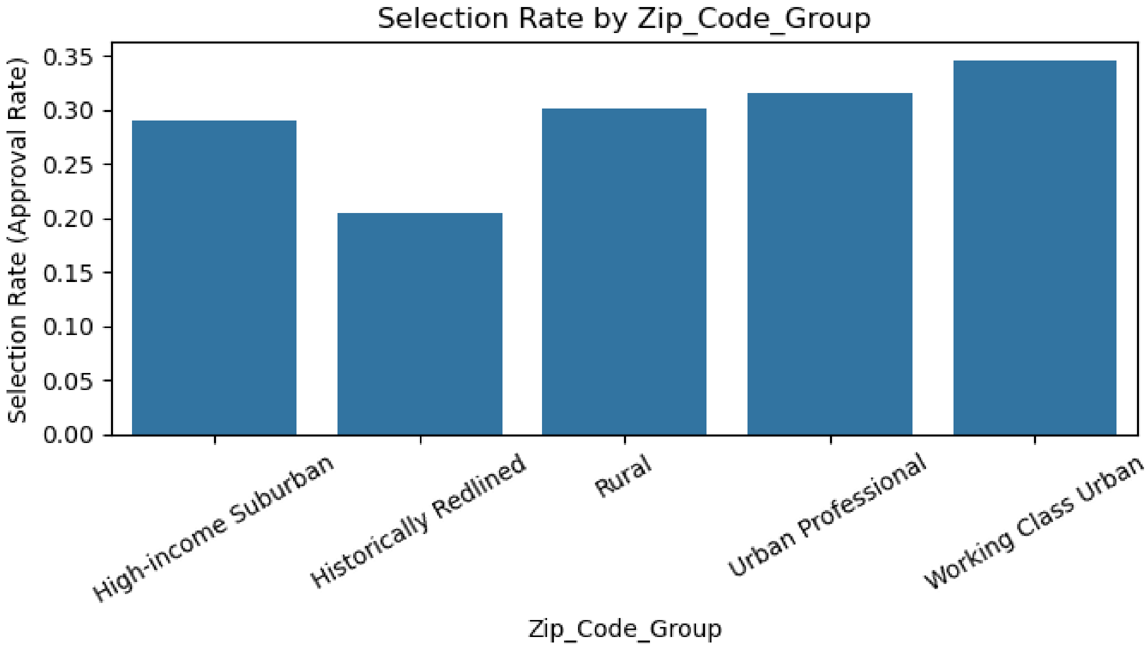
- `charts/selection_rate_by_Income.png`



  - `charts/selection_rate_by_Age.png`



  - `charts/selection_rate_by_Zip_Code_Group.png`



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6. Real-World Implications

- **At Risk:**
  - Black, Native American, and low-income applicants are much less likely to be approved.
  - Residents of historically redlined areas are also disadvantaged.
- **Ethical/Social Consequences:**
  - Perpetuates existing inequalities
  - May violate anti-discrimination laws
  - Erodes trust in automated decision systems
- **Fairness Audit:**

- Based on current metrics, the model may not pass a strict regulatory fairness audit without further mitigation.

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7. Limitations & Reflections

- **What didn't work:**
  - Some fairness metrics remain suboptimal despite class balancing and feature engineering.
  - Demographic parity difference for income is extremely high, indicating the model is highly sensitive to income.
- **Next Steps:**
  - Try additional fairness mitigation (e.g., reweighting, post-processing)
  - Explore more interpretable models or explainability tools (e.g., SHAP)
- **Lessons Learned:**
  - Fairness auditing is essential and non-trivial
  - Group-level metrics can mask individual-level unfairness
  - Continuous monitoring and improvement are needed