

# D-BIAS Analysis Report

heart.csv

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Fairness Score: 42/100

Fairness Label: Poor

Bias Risk: High

## Detected Biases

- Categorical Imbalance (col: sex) – High
- Categorical Imbalance (col: fbs) – High
- Categorical Imbalance (col: exang) – Moderate
- Numeric Correlation Bias (col: age ✕ ca) – Moderate
- Numeric Correlation Bias (col: oldpeak ✕ num) – Moderate
- Numeric Correlation Bias (col: ca ✕ num) – Moderate
- Outlier Bias (col: chol) – High

## Recommendations

- **Prioritize Data Augmentation:** The most effective solution is to collect more data, specifically targeting the underrepresented groups: **female patients** and individuals with **high fasting blood sugar**.
- **Clean and Preprocess Data:** **Investigate `chol` Outliers:** Examine the 20% of `chol` outliers. Correct or remove clear errors (e.g., `chol`=0) and apply robust scaling or transformations to mitigate the influence of remaining extremes.
- **Use Advanced Sampling:** For `sex` and `fbs`, apply techniques like **SMOTE (Synthetic Minority Over-sampling Technique)** to generate new, synthetic data points for the minority classes, creating a more balanced training set.
- **Employ Fair Modeling Practices:** **Use Class Weights:** During training, assign higher weights to the minority classes ('sex`='Female', `fbs`='True') to force the model to prioritize learning their patterns.
- **Evaluate Fairness Metrics:** Do not rely solely on overall accuracy. Evaluate the model's performance (e.g., recall, precision, F1-score) **separately for each gender** and for each category of `fbs` and `exang` to ensure equitable performance.
- **Promote Model Interpretability:** For correlated features like `age` ✕ `ca` use models that are either robust to multicollinearity or use techniques like regularization.
- **Analyze feature importances:** to ensure the model does not become overly reliant on single predictors like `ca` or `oldpeak`.

## Conclusion

The dataset's "fairness health score" is **Poor**. It suffers from critical biases related to representation and data quality that must be resolved before it can be responsibly used to develop a fair and effective clinical prediction tool.