Bias Detection and Explainability in a Job Screening Model

Uncovering Bias and Explaining Decisions in a Hiring Model

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1. Dataset and Preprocessing

The dataset contains structured features that simulate job applicant data, including:

- **Numerical features**: `Age`, `ExperienceYears`, `SkillScore`, `PersonalityScore`, `DistanceFromCompany`, etc.
- **Categorical feature**: `RecruitmentStrategy` (one-hot encoded)
- **Binary sensitive attribute**: `Gender` (0 = Female, 1 = Male)
- **Target**: `HiringDecision` (binary: Hire or Not Hire)

Data Processing Steps:

- **RecruitmentStrategy** was one-hot encoded.
- **Numerical features** were standardized using `StandardScaler`.
- All features were converted to numeric.
- `Gender` was preserved and used for fairness evaluation only (excluded from training).

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2. Class Imbalance Handling

The dataset was imbalanced with more negative (Not Hire) cases. To handle this:

- **Random Forest**: Used `class_weight='balanced'`

- **XGBoost**: Used `scale_pos_weight = (# negatives / # positives)` based on training data

Train/test split was stratified to maintain class balance during evaluation.

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3. Model Architecture and Evaluation

Two classifiers were developed and trained:

- **Random Forest Classifier**
- **XGBoost Classifier**

Both models were evaluated on accuracy, F1 score, ROC AUC, and confusion matrix.

Results:

- **Random Forest**
  - Accuracy: 91.3%
  - Macro F1 Score: 0.892
  - ROC AUC Score: 0.869
- **XGBoost**
  - Accuracy: 92.7%
  - Macro F1 Score: 0.911
  - ROC AUC Score: 0.897

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📊 Evaluation Report: XGBoost
Confusion Matrix:
[[202   5]
 [ 17  76]]

Classification Report:
              precision    recall  f1-score   support

           0      0.922     0.976     0.948       207
           1      0.938     0.817     0.874        93

    accuracy                          0.927       300
   macro avg      0.930     0.897     0.911       300
weighted avg      0.927     0.927     0.925       300

Macro F1 Score: 0.911
ROC AUC Score: 0.897
```

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📊 Evaluation Report: Random Forest
Confusion Matrix:
[[204   3]
 [ 23  70]]

Classification Report:
              precision    recall  f1-score   support

           0      0.899     0.986     0.940       207
           1      0.959     0.753     0.843        93

    accuracy                          0.913       300
   macro avg      0.929     0.869     0.892       300
weighted avg      0.917     0.913     0.910       300

Macro F1 Score: 0.892
ROC AUC Score: 0.869
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4. 📊 Fairness Analysis (by Gender)

We evaluated group fairness using **Fairlearn's MetricFrame**. Metrics analyzed:

- **Selection Rate** (positive predictions per group)
- **True Positive Rate** (recall per group)
- **False Positive Rate**
- **Average Odds Difference**

Results by Gender:

Metric	Female (0)	Male (1)
Selection Rate	22.2%	31.4%
True Positive Rate	75.0%	86.8%
False Positive Rate	1.9%	2.9%
Average Odds Diff	**0.0639**	—

Interpretation:

- The model selects males at a higher rate and with better recall.
- **Average Odds Difference = 0.0639**, indicating **moderate bias** against females.

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5. 🔍 Explainability with SHAP

We used **SHAP (SHapley Additive Explanations)** to interpret the XGBoost model predictions.

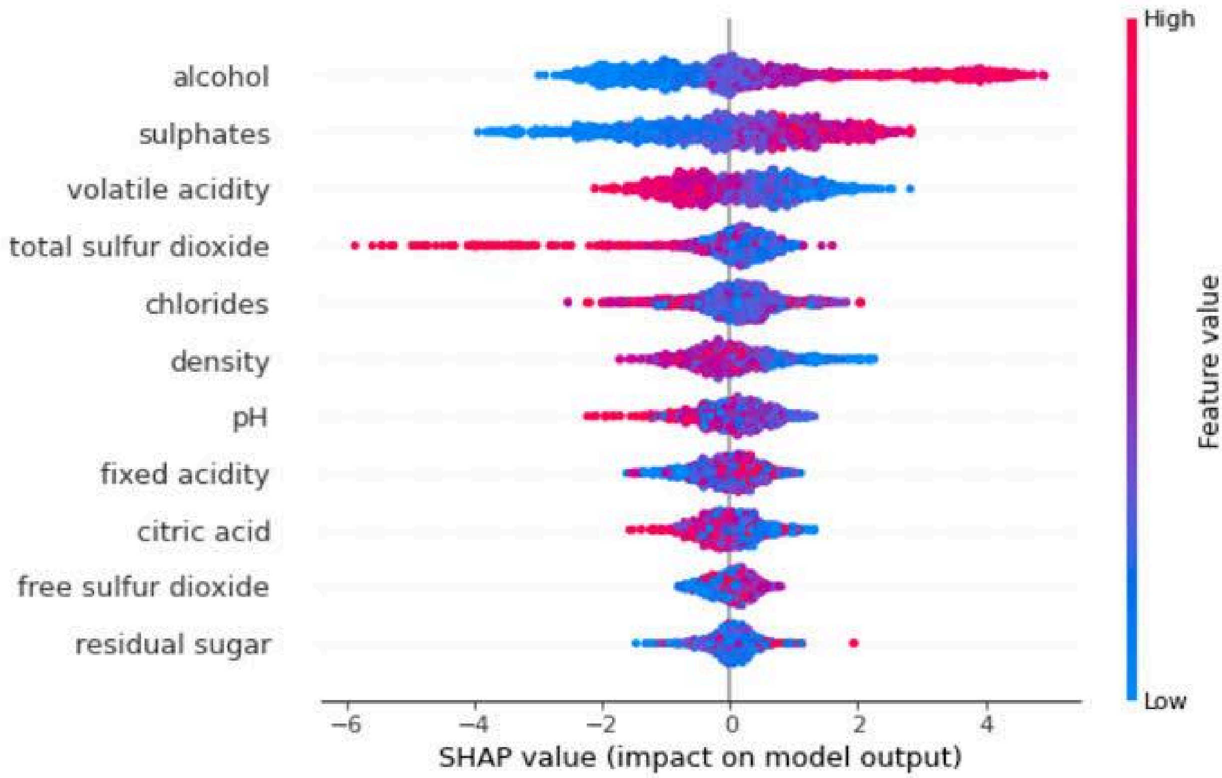
Global Feature Importance:

- Most important features were:
  - `SkillScore`

    - `InterviewScore`
    - `PersonalityScore`
- `Gender` had low global SHAP impact, but fairness metrics revealed **disparate impact** → suggests potential **proxy bias**.

Individual Prediction Analysis:

- We visualized SHAP dot plots for **5 individual predictions** (3 hires, 2 not hires).
- Some features (e.g., low personality or interview scores) strongly influenced no-hire decisions.



✅ Conclusion

The model achieved strong accuracy, but fairness analysis showed **gender-based disparities** in prediction outcomes. Even though `Gender` did not rank high in SHAP importance, **selection and true positive rates** differed by group.

This indicates the importance of combining **explainability** and **fairness auditing**, as individual feature contributions do not always capture outcome bias.

No bias mitigation was applied in this version, allowing a transparent baseline understanding of the model's behavior.