Fairness, Explainability & Ethical AI: Model Analysis Report Introduction to Ethical AI

Ethical Artificial Intelligence focuses on building systems that are fair, transparent, and accountable. Bias in data and models can lead to unfair outcomes for specific groups, especially when sensitive attributes such as gender, race, or age are involved. This project evaluates a classification model not only by accuracy, but also by how fair and explainable its decisions are, using Fairlearn, SHAP, and LIME.

Dataset Description & Preprocessing

The dataset used in this study is the Adult Income Dataset (UCI), which predicts whether a person earns > $50K annually.

Preprocessing Steps

Removed missing values (“?”).

One-hot encoded categorical variables using pd.get_dummies(drop_first=True).

Scaled numerical variables using StandardScaler().

Target variable:

0 = <=50K

1 = >50K

Sensitive attribute selected for fairness analysis:

Sex (0 = Female, 1 = Male)

Final shape after encoding:

100 features, thousands of samples.

Model Training & Evaluation

A Logistic Regression classifier was trained with 200 iterations.

Performance Metrics Metric Score Accuracy 0.8537 Precision (>50K) 0.74 Recall (>50K) 0.61 F1-Score (>50K) 0.67 Confusion Matrix [[6902 515] [914 1438]]

Interpretation

The model performs well overall.

It is better at identifying <=50K earners than >50K earners.

This imbalance is common due to class distribution.

Fairness Analysis (Using Fairlearn)

The model was evaluated across the sensitive attribute Sex.

Metrics by Group Sex Selection Rate False Positive Rate True Positive Rate Female (0) 0.0847 0.0249 0.5587 Male (1) 0.2560 0.0970 0.6208 Key Findings

Selection rate for males (25.6%) is 3× higher than for females (8.4%) → Model is more likely to predict >50K for men.

False positive rate is higher for men, meaning men are incorrectly labeled as high earners more often.

True positive rate also favors men, showing performance advantage.

Conclusion

The model displays gender bias, performing better for men across all fairness metrics.

Explainability Analysis SHAP (Global Explainability)

SHAP values showed the most influential features globally:

marital-status_Married-civ-spouse

capital-gain

education-num

sex_Male

age

Insights

Married individuals strongly contribute to >50K predictions.

sex_Male shows noticeable impact → gender is influencing predictions.

Higher education, age, and capital gain predict higher income.

SHAP Waterfall (Local Explanation)

For an individual instance:

Features like marital status, occupation, and sex_Male increased the income prediction.

Others like lower education-num reduced it.

LIME (Local Explainability)

LIME highlighted:

Positive contributors (e.g., occupation, marital status)

Negative contributors (e.g., low capital gain, lower education)

Both SHAP and LIME confirm consistent influential features, improving trust through transparency.

Ethical Considerations & Recommendations What the results show

The model is accurate but not fair across gender.

Sensitive attribute ("sex") influences the outcome indirectly through encoded variables.

The imbalance in true/false positive rates indicates systemic gender bias.

Recommendations

✓ Apply fairness constraints (equalized odds / demographic parity) using Fairlearn mitigation. ✓ Remove or limit sensitive leakage features (occupation, marital-status patterns). ✓ Re-sample the dataset to balance gender distribution. ✓ Consider fairness-aware algorithms (e.g., adversarial debiasing). ✓ Continuously monitor fairness metrics during deployment.

Conclusion

This project demonstrates the importance of combining predictive performance with fairness and explainability. While Logistic Regression performs well overall, fairness metrics reveal gender bias, and explainability tools (SHAP + LIME) confirm that both gender and gender-correlated features influence predictions.

Improving this model requires incorporating fairness constraints, revisiting preprocessing decisions, and continuously evaluating ethical impacts to ensure an equitable AI system.

```
!pip install fairlearn shap lime
```

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Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.12/dist-packages (from python-dateutil>=2.8.2->pandas>=2.0.3->
```

```python
import pandas as pd
import numpy as np

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report

from fairlearn.metrics import MetricFrame, selection_rate, false_positive_rate, true_positive_rate

import shap
import matplotlib.pyplot as plt
from lime.lime_tabular import LimeTabularExplainer

# Make plots show in the notebook
%matplotlib inline
```

```python
# Column names for the Adult dataset
cols = [
    "age","workclass","fnlwgt","education","education-num",
    "marital-status","occupation","relationship","race","sex",
    "capital-gain","capital-loss","hours-per-week","native-country","income"
]

# ✅ Working URL from UCI
url = "https://archive.ics.uci.edu/ml/machine-learning-databases/adult/adult.data"

# Load dataset
df = pd.read_csv(
    url,
    names=cols,
    na_values=" ?",
    skipinitialspace=True
)

# Drop rows with missing values
df.dropna(inplace=True)

df.head()
```

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationship	race	sex	capital-gain	capital-loss	hours-per-week
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	2174	0	40
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	13
2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	0	0	40
3	53	Private	234721	11th	7	Married-civ-	Handlers-cleaners	Husband	Black	Male	0	0	40

Next steps: Generate code with df New interactive sheet

```python
# Sensitive attribute
sensitive_feature_name = "sex"

# ✅ Correct target: strip spaces and compare
y = (df["income"].str.strip() == ">50K").astype(int)

# Features (drop the target)
X = df.drop("income", axis=1)

# One-hot encode categorical variables
X_encoded = pd.get_dummies(X, drop_first=True)

# Sensitive attribute: 1 = Male, 0 = Female
sensitive_feature = (df["sex"].str.strip() == "Male").astype(int)
```

```
# Optional: check class balance
print(y.value_counts())
X_encoded.head()
```

```
income
0    24720
1     7841
Name: count, dtype: int64
```

	age	fnlwgt	education-num	capital-gain	capital-loss	hours-per-week	workclass_Federal-gov	workclass_Local-gov	workclass_Never-worked	workclass_Private
0	39	77516	13	2174	0	40	False	False	False	False
1	50	83311	13	0	0	13	False	False	False	False
2	38	215646	9	0	0	40	False	False	False	True
3	53	234721	7	0	0	40	False	False	False	True
4	28	338409	13	0	0	40	False	False	False	True

5 rows × 100 columns

```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

# Train-test split (also split the sensitive feature)
X_train, X_test, y_train, y_test, s_train, s_test = train_test_split(
    X_encoded,
    y,
    sensitive_feature,
    test_size=0.3,
    random_state=42,
    stratify=y
)

# Scale features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

print("Train shape:", X_train.shape, " Test shape:", X_test.shape)
print("y_train value counts:\n", y_train.value_counts())
```

```
Train shape: (22792, 100)  Test shape: (9769, 100)
y_train value counts:
 income
0    17303
1     5489
Name: count, dtype: int64
```

```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report

model = LogisticRegression(max_iter=200)
model.fit(X_train_scaled, y_train)

y_pred = model.predict(X_test_scaled)

print("✅ Model trained")

# Quick check
print("Sample predictions:", y_pred[:10])
```

```
✅ Model trained
Sample predictions: [0 0 0 0 1 0 0 0 0 0]
```

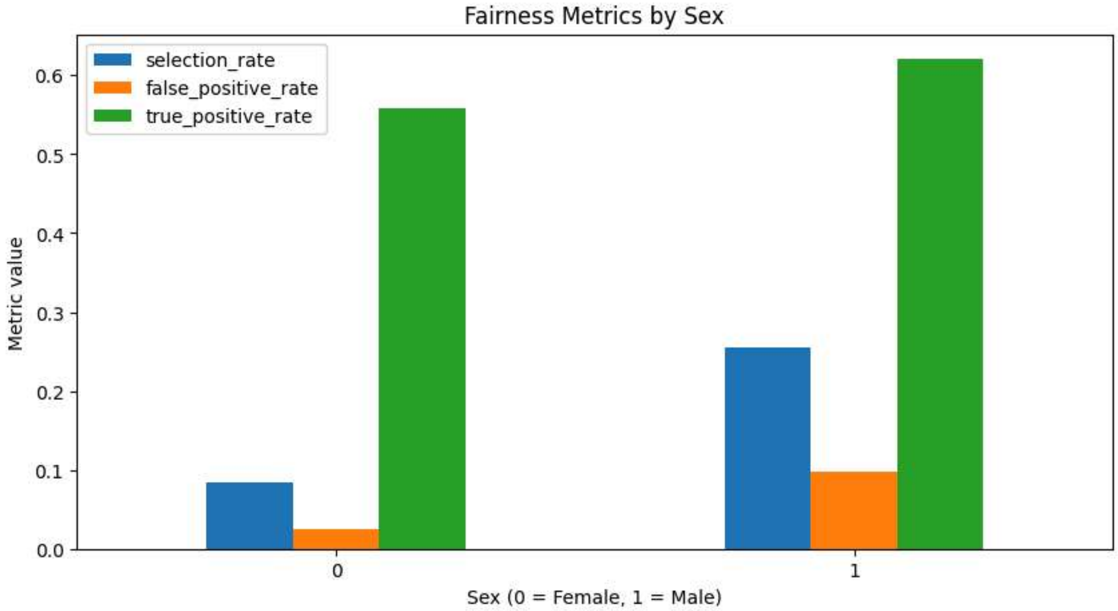
```
print("Accuracy:", accuracy_score(y_test, y_pred))

print("\nClassification Report:\n")
print(classification_report(y_test, y_pred))

print("\nConfusion Matrix:\n")
```

```
print(confusion_matrix(y_test, y_pred))
```

```
Accuracy: 0.8537209540382844

Classification Report:

              precision    recall  f1-score   support

           0       0.88      0.93      0.91      7417
           1       0.74      0.61      0.67      2352

    accuracy                           0.85      9769
   macro avg       0.81      0.77      0.79      9769
weighted avg       0.85      0.85      0.85      9769


Confusion Matrix:

[[6902  515]
 [ 914 1438]]
```

```
from fairlearn.metrics import MetricFrame, selection_rate, false_positive_rate, true_positive_rate
import matplotlib.pyplot as plt

metrics_dict = {
    "selection_rate": selection_rate,
    "false_positive_rate": false_positive_rate,
    "true_positive_rate": true_positive_rate
}

mf = MetricFrame(
    metrics=metrics_dict,
    y_true=y_test,
    y_pred=y_pred,
    sensitive_features=s_test  # 1 = Male, 0 = Female
)

print("=== Fairness metrics by group (0 = Female, 1 = Male) ===")
print(mf.by_group)

# Bar plot for visual comparison
mf.by_group.plot(kind="bar", figsize=(10, 5))
plt.title("Fairness Metrics by Sex")
plt.xlabel("Sex (0 = Female, 1 = Male)")
plt.ylabel("Metric value")
plt.xticks(rotation=0)
plt.show()
```

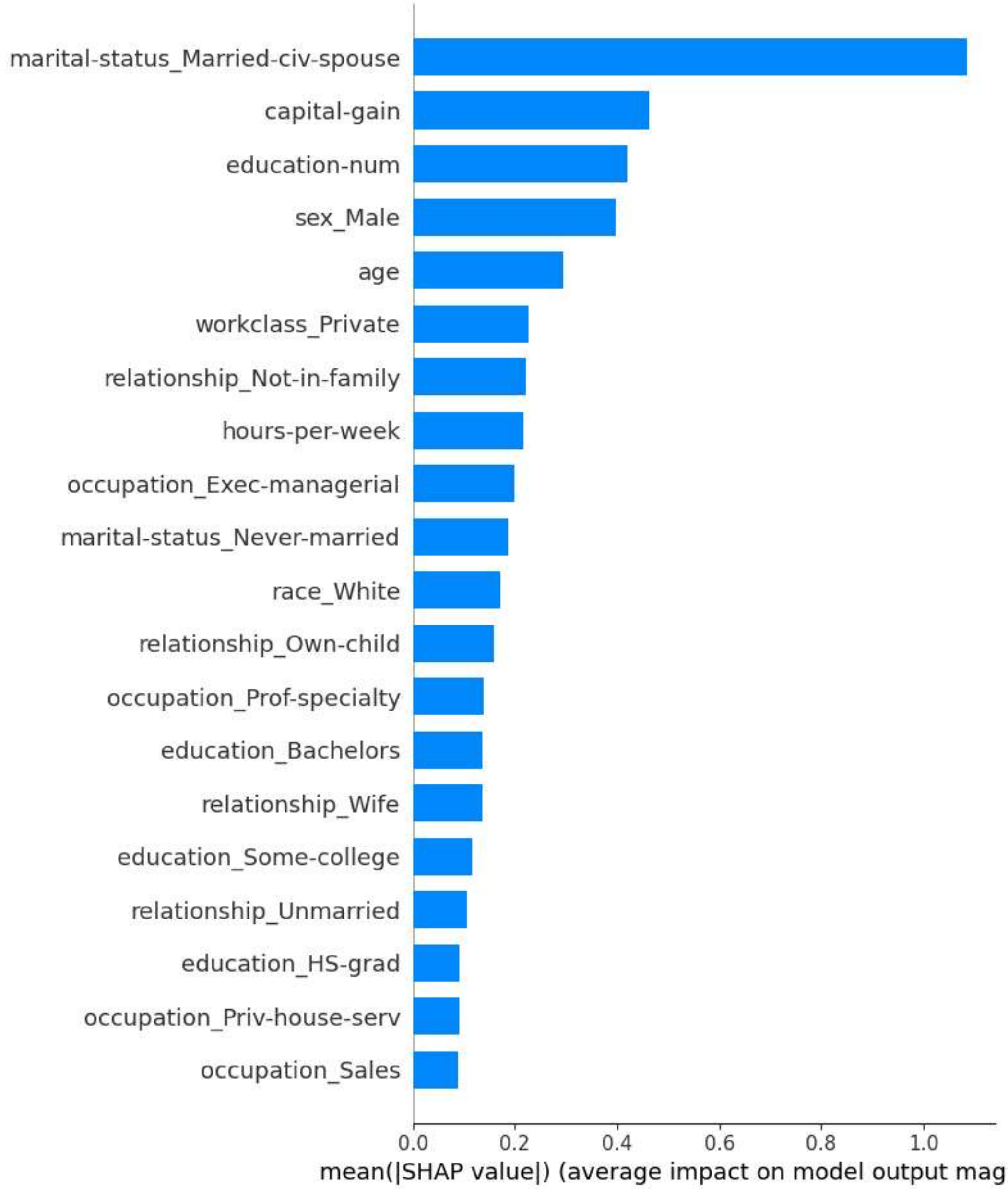
```
=== Fairness metrics by group (0 = Female, 1 = Male) ===
     selection_rate  false_positive_rate  true_positive_rate
sex
0          0.084714             0.024991            0.558659
1          0.256012             0.097028            0.620863
```



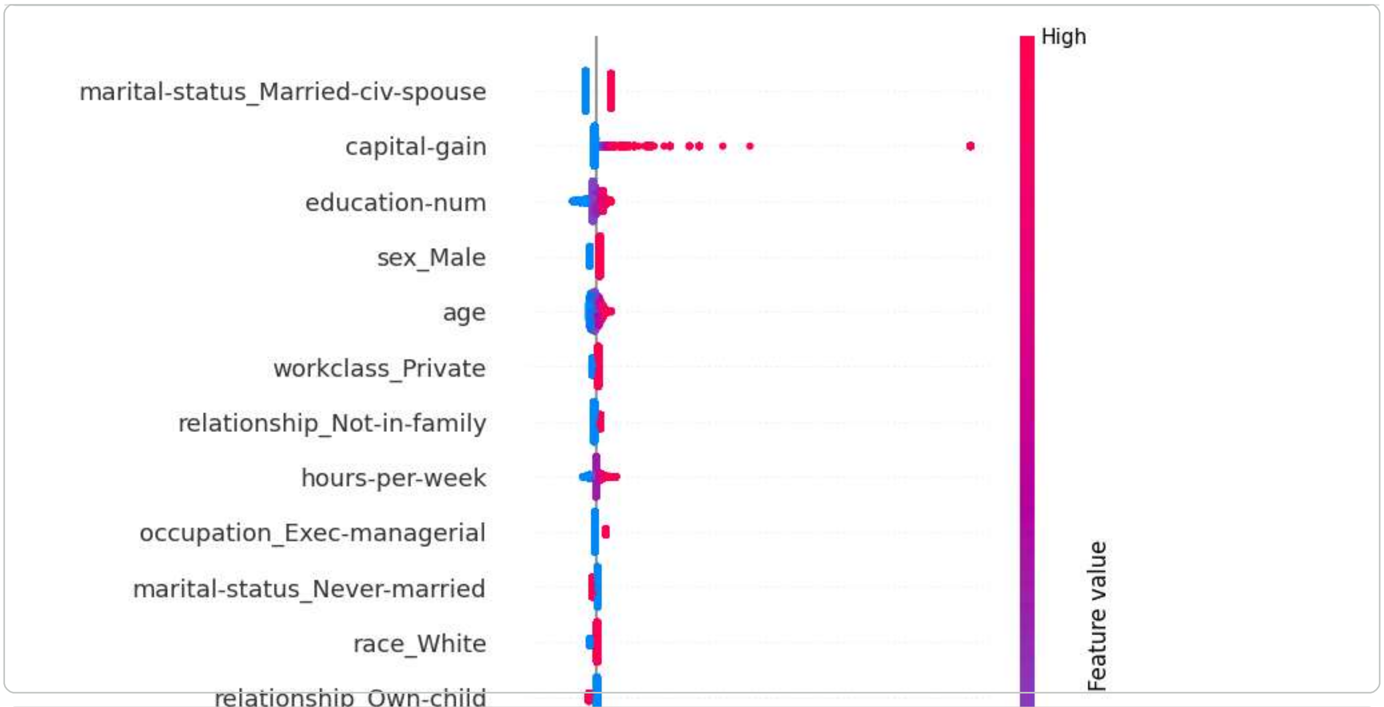

```
import shap

explainer = shap.LinearExplainer(model, X_train_scaled)
shap_values = explainer.shap_values(X_test_scaled)
print("SHAP values shape:", np.array(shap_values).shape)
```

```
SHAP values shape: (9769, 100)
```

```
shap.summary_plot(shap_values, X_test, plot_type="bar")
```




```
shap.summary_plot(shap_values, X_test)
```




```
i = 0  # index of the instance you want to explain

shap.waterfall_plot(
    shap.Explanation(
        values=shap_values[i],
        base_values=explainer.expected_value,
        data=X_test.iloc[i],
        feature_names=X_test.columns
    )
)
```