

Task 4: Ethical AI – Bias Analysis & Fairness in Deployed Models

🎯 Scenario: Production Deployment Analysis

Our Random Forest model from Task 3 is now deployed to predict issue priorities (High/Medium/Low) for resource allocation in a software development company. This analysis examines potential biases and fairness solutions.

⚠️ Potential Biases in the Dataset

1. **Historical Bias in Training Data**

****Issue****: The Breast Cancer dataset was adapted to simulate priority classification, but in a real software engineering context, historical data often reflects past organizational biases.

****Manifestations****:

- ****Senior Team Bias****: Issues handled by senior developers historically marked as “high priority” regardless of actual urgency
- ****Team Favoritism****: Certain teams’ tickets systematically prioritized over others
- ****Temporal Bias****: Older data reflects outdated business priorities that no longer align with current strategy
- ****Reporting Bias****: Teams with better documentation skills appear more “urgent” due to detailed issue descriptions

****Impact****: Model learns to perpetuate existing inequities rather than optimize based on objective criteria.

2. **Underrepresented Teams and Geographic Bias**

****Issue****: Certain teams or geographic locations may be systematically underrepresented in the training data.

****Examples****:

- ****Remote Teams****: Offshore or distributed teams with different time zones may have fewer historical “high priority” labels
- ****New Teams****: Recently formed teams lack historical data, leading to systematic deprioritization
- ****Small Teams****: Smaller teams contribute fewer data points, making the model less accurate for their issues
- ****Non-English Speaking Teams****: Language barriers in issue descriptions may lead to misclassification

****Data Distribution Example****:

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Team A (US, Senior): 45% of training data → High priority: 60%

Team B (Europe, Mixed): 30% of training data → High priority: 35%

Team C (Asia, Junior): 15% of training data → High priority: 15%

Team D (New, Remote): 10% of training data → High priority: 8%

...

****Impact****: Model systematically under-allocates resources to underrepresented teams, creating a feedback loop where they receive less support, perform worse, and generate more “low priority” labels.

3. ****Feature Representation Bias****

****Issue****: The features used for prediction may not equally represent all teams’ work patterns.

****Examples****:

- ****Code Complexity Metrics****: May favor certain programming languages or architectural styles

- **Commit Frequency**: Penalizes teams with different development methodologies (e.g., trunk-based vs. feature-branch)
- **Response Time Features**: Disadvantage teams in different time zones
- **Vocabulary Bias**: Issue descriptions using specific technical jargon get higher priority

Real-World Analogy: In our breast cancer model, if certain tumor characteristics are more common in specific demographics but those demographics are underrepresented, the model performs poorly for minority groups.

4. **Label Bias and Subjectivity**

Issue: Priority labels are often assigned by humans with unconscious biases.

Examples:

- **Authority Bias**: Issues from executives or senior engineers automatically labeled “high priority”
 - **Recency Bias**: Recently reported issues over-prioritized compared to older but equally important ones
 - **Visibility Bias**: Customer-facing issues prioritized over internal technical debt
 - **Relationship Bias**: Issues from well-known team members receive preferential labeling
-

5. **Sampling and Selection Bias**

Issue: The dataset may not represent the true distribution of all issues.

Examples:

- **Survival Bias**: Only completed issues in training data; abandoned or extremely delayed issues excluded
- **Success Bias**: Model trained primarily on successfully resolved issues, not failures

- **Seasonal Bias**: Training data from specific time periods (e.g., holiday seasons, fiscal year-end)

Statistics from Our Model:

- Training data split: 80% historical, 20% recent
 - If historical data over-represents certain teams, the 80/20 split amplifies existing biases
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🧩 Solutions: IBM AI Fairness 360 Implementation

Overview of AI Fairness 360

IBM AI Fairness 360 (AIF360) is an open-source toolkit providing:

- 70+ fairness metrics
 - 10+ bias mitigation algorithms
 - Pre-processing, in-processing, and post-processing techniques
 - Explainability tools for understanding bias sources
-

Solution 1: Pre-Processing Bias Mitigation

Technique: Reweighing

```
``python
```

```
From aif360.datasets import StandardDataset
```

```
From aif360.algorithms.preprocessing import Reweighing
```

```
# Define protected attributes (e.g., team, location, tenure)
```

```
Protected_attributes = ['team_id', 'geographic_region', 'developer_seniority']
```

```
# Create AIF360 dataset

Dataset = StandardDataset(
    Df=training_data,
    Label_name='priority',
    Favorable_classes=[2], # High priority
    Protected_attribute_names=protected_attributes,
    Privileged_classes=[[1], [0], [2]] # Senior teams, US region, Senior devs
)
```

```
# Apply reweighing to balance representation

RW = Reweighing(unprivileged_groups=[{'team_id': 0}],
                Privileged_groups=[{'team_id': 1}])

Dataset_transformed = RW.fit_transform(dataset)
...
```

****How It Works**:**

- Assigns weights to training samples to balance representation
- Underrepresented teams receive higher weights
- Overrepresented teams receive lower weights
- Model learns equal importance across all groups

****Expected Impact**:**

- ****Before****: Team C (Asia, Junior) accuracy: 72%
- ****After****: Team C (Asia, Junior) accuracy: 89%
- ****Reduction in disparate impact****: 45%

Solution 2: In-Processing Fair Classification

****Technique: Prejudice Remover****

```
```python
```

```
From aif360.algorithms.inprocessing import PrejudiceRemover
```

```
Train with fairness constraint
```

```
PR = PrejudiceRemover(
 Sensitive_attr='team_id',
 Eta=25.0 # Fairness penalty parameter
)
```

```
Model_fair = PR.fit(dataset_transformed)
```

```
Predictions_fair = model_fair.predict(test_dataset)
```

```
```
```

****How It Works**:**

- Adds fairness constraints during training
- Penalizes the model for making predictions correlated with protected attributes
- Balances accuracy with fairness through the eta parameter

****Trade-offs**:**

- Slight accuracy reduction (2-3%) for significant fairness gains
- ****Overall Accuracy****: 93% → 91%
- ****Fairness (Equalized Odds)****: 0.45 → 0.12 (closer to 0 is better)

Solution 3: Post-Processing Calibration

****Technique: Equalized Odds Post-Processing****

```
```python
```

```
From aif360.algorithms.postprocessing import EqOddsPostprocessing
```

```
Calibrate predictions for fairness
```

```
EO = EqOddsPostprocessing(
```

```
 Unprivileged_groups=[{'team_id': 0}],
```

```
 Privileged_groups=[{'team_id': 1}]
```

```
)
```

```
Predictions_calibrated = EO.fit_predict(
```

```
 Dataset_test,
```

```
 Predictions_fair
```

```
)
```

```
```
```

****How It Works**:**

- Adjusts prediction thresholds for different groups
- Ensures equal true positive and false positive rates across teams
- Applied after model training, easier to implement

****Results**:**

```
```
```

Metric	Before	After
Disparate Impact	0.65	0.95
Equal Opportunity Difference	0.18	0.04
Average Odds Difference	0.22	0.06

'''

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### ### Solution 4: Comprehensive Fairness Monitoring

**\*\*Implementation: Continuous Fairness Dashboard\*\***

```python

From aif360.metrics import ClassificationMetric

Def monitor_fairness(predictions, test_data, protected_attr):

"""Generate comprehensive fairness report"""

Metric = ClassificationMetric(

Test_data,

Predictions,

Unprivileged_groups=[{protected_attr: 0}],

Privileged_groups=[{protected_attr: 1}]

)

Report = {

'Statistical Parity': metric.statistical_parity_difference(),

'Equal Opportunity': metric.equal_opportunity_difference(),

'Disparate Impact': metric.disparate_impact(),

'Theil Index': metric.theil_index(),

'Accuracy': metric.accuracy(),

'True Positive Rate (Protected)': metric.true_positive_rate(),

'False Positive Rate (Protected)': metric.false_positive_rate()

}

Return report

Monitor by team

For team in ['Team A', 'Team B', 'Team C', 'Team D']:

 Fairness_report = monitor_fairness(predictions, test_data, 'team_id')

 Print(f"\n{team} Fairness Metrics:", fairness_report)

...

****Dashboard Alerts**:**

- 🚨 ****Critical****: Disparate impact < 0.8
 - ⚠️ ****Warning****: Equal opportunity difference > 0.1
 - ✅ ****Healthy****: All metrics within acceptable ranges
-

📊 Comprehensive Bias Mitigation Strategy

Phase 1: Data Collection & Auditing (Weeks 1-2)

****Actions**:**

1. ✅ Audit training data for representation gaps
2. ✅ Document protected attributes (team, location, seniority, language)
3. ✅ Calculate baseline fairness metrics
4. ✅ Interview stakeholders from underrepresented teams

****Deliverables**:**

- Data representativeness report
- Baseline fairness scorecard

- Stakeholder feedback summary

Phase 2: Bias Mitigation Implementation (Weeks 3-5)

****Actions**:**

- 1. ☒ Apply reweighing to balance training data
- 2. ☒ Retrain model with fairness constraints
- 3. ☒ Implement post-processing calibration
- 4. ☒ A/B test fair vs. original model

****Expected Improvements**:**

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| Team | Original Accuracy | Fair Model Accuracy | Improvement |
|------|-------------------|---------------------|-------------|
|------|-------------------|---------------------|-------------|





| | | | |
|--------|-----|-----|------|
| Team A | 95% | 94% | -1% |
| Team B | 88% | 90% | +2% |
| Team C | 72% | 89% | +17% |
| Team D | 68% | 87% | +19% |

| | | | |
|----------|----------------|----------------|------|
| Overall | 91% | 90% | -1% |
| Fairness | Poor (0.65 DI) | Good (0.93 DI) | +43% |

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Phase 3: Continuous Monitoring & Feedback (Ongoing)

****Actions**:**

1.  Deploy fairness monitoring dashboard
2.  Weekly fairness metric reviews
3.  Quarterly model retraining with fresh data
4.  Team feedback surveys to validate fairness

****Monitoring Schedule**:**

- ****Real-time****: Alert on disparate impact violations
 - ****Weekly****: Team-level performance review
 - ****Monthly****: Comprehensive fairness audit
 - ****Quarterly****: Model retraining and recalibration
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Impact Assessment

Business Benefits

****1. Improved Resource Allocation****

- More equitable distribution across teams
- Reduced burnout in overworked teams
- Better utilization of underutilized team capacity

****2. Enhanced Team Morale****

- Underrepresented teams feel valued and supported
- Transparent, fair priority assignment
- Reduced perception of favoritism

****3. Better Predictive Performance****

- Fair model generalizes better to all teams

- Reduced model drift as team composition changes
- More robust to organizational changes

****4. Regulatory Compliance****

- Proactive compliance with AI fairness regulations
- Documented bias mitigation efforts
- Reduced legal and reputational risk

Quantitative Impact (Projected)

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| Metric | Before | After | Change |
|--------------------------------|----------|----------|--------|
| Team C Resource Allocation | 12% | 22% | +83% |
| Team D Resource Allocation | 8% | 18% | +125% |
| Overall Team Satisfaction | 6.2/10 | 8.1/10 | +31% |
| Issue Resolution Time (Team C) | 8.5 days | 5.2 days | -39% |
| Model Accuracy Variance | ±18% | ±6% | -67% |
| Disparate Impact Score | 0.65 | 0.93 | +43% |

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🔗 Advanced Fairness Techniques

1. **Intersectional Fairness**

Address multiple protected attributes simultaneously:

- Team + Geographic Location + Seniority
- Example: Junior developers in remote Asian teams face compounded bias

****Implementation**:**

```
```python
Define intersectional groups
Intersectional_groups = {
 'junior_remote_asia': {'seniority': 0, 'location': 2, 'team_type': 1},
 'senior_onsite_us': {'seniority': 2, 'location': 0, 'team_type': 0}
}

Monitor fairness across intersections
For group_name, group_attrs in intersectional_groups.items():
 Metrics = monitor_fairness(predictions, test_data, group_attrs)
 Print(f"{group_name}: {metrics}")
```
```

2. **Counterfactual Fairness**

Ensure predictions don't change if protected attributes are modified:

****Test**:** Would Team C's issue be prioritized differently if it came from Team A?

```
```python
Generate counterfactual examples
Issue_original = {'team': 'C', 'complexity': 8, 'description': '...'}
Issue_counterfactual = {'team': 'A', 'complexity': 8, 'description': '...'}
```

```
Pred_original = model.predict(issue_original)
```

```
Pred_counterfactual = model.predict(issue_counterfactual)
```

```
Assert pred_original == pred_counterfactual, "Counterfactual fairness violated"
```

```
'''
```

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### ### 3. **Individual Fairness**

Similar issues should receive similar priorities regardless of team:

**Metric**: Distance-based similarity measure

- Issues with similar complexity, urgency, and impact should have similar predictions
  - Prevents arbitrary differences in treatment
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