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Algorithmic Bias in Military AI Systems: Challenges and Solutions for Fair and Accurate Decision-Making

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Abstract: This paper examines algorithmic bias in AI systems used for military decision-making, identifies key sources of unfairness, and demonstrates practical mitigation strategies with implemented machine-learning experiments. We generate a synthetic but realistic dataset that mimics decisions (e.g., target identification / threat classification) with a binary sensitive attribute (e.g., group A vs group B). We implement baseline classifiers (Logistic Regression, Random Forest), measure fairness-related metrics (statistical parity difference, equal opportunity difference, disparate impact), and apply two mitigation strategies: reweighing (pre-processing) and group-specific thresholding (post-processing). Results include accuracy, fairness trade-offs, and visualizations. The paper ends with recommendations and limitations.

Keyword: Algorithmic bias, fairness, military AI, reweighing, thresholding, fairness metrics, machine learning.

I. INTRODUCTION

AI systems are increasingly used in high-stakes military contexts — surveillance, target identification, resource allocation, and autonomous systems control. Biases in data or algorithmic choices can lead to unfair outcomes: systematically higher false-positive rates for certain groups, misclassification of civilians as threats, or unequal allocation of surveillance resources. This paper explores these risks and demonstrates concrete mitigation approaches via experiments.

II. PROBLEM STATEMENT AND THREAT MODEL

We consider a supervised binary classification task (Threat vs non-Threat). The data contain a sensitive binary attribute S (0/1) representing demographic or equipment-type groups. Our threat model assumes that erroneous or biased decisions can cause disproportionate harm to the disadvantaged group (higher false positives leading to unwarranted engagement, or higher false negatives leading to missed genuine threats).

III. SOURCES OF ALGORITHMIC BIAS IN MILITARY AI

1. Historical labeling bias — human labels reflect past prejudices.
2. Sampling bias — training sensors collect more data for one group/region.
3. Measurement bias — sensor differences (e.g., thermal vs optical) cause attribute shifts.
4. Modeling bias — using loss functions that ignore fairness costs.

5. Deployment/context shifts — environment changes leading to degraded fairness.

IV. FAIRNESS DEFINITIONS (SELECTED)

Statistical parity difference (SPD) = $P(\hat{Y}=1|S=0) - P(\hat{Y}=1|S=1)$.
Equal opportunity difference (EOD) = $TPR(S=0) - TPR(S=1)$.
Disparate impact (DI) = $P(\hat{Y}=1|S=1) / P(\hat{Y}=1|S=0)$.
A fair system is contextual — sometimes parity is desired, other times equal opportunity (equal TPR) is more relevant.

V. EXPERIMENT: DATASET & METHODS

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5.1 Synthetic dataset rationale

To demonstrate methods reproducibly and avoid sensitive operational data, we generate a synthetic dataset that captures realistic characteristics: correlated features, an explicit sensitive attribute, and label noise.

5.2 Data generation (concept)

Features: 8 continuous features drawn from group-specific distributions (to simulate measurement or demographic differences).
Sensitive attribute $S \in \{0,1\}$ with 40% in S=1 (group B).
Labels generated from an underlying logistic function of features + group-dependent bias term to simulate historical bias.

5.3 Methods implemented

Baseline: Logistic Regression (LR), Random Forest (RF).
Mitigation A (pre-processing): Reweighing samples to balance favorable outcomes across groups.
Mitigation B (post-processing): Group-specific thresholding (choose separate score thresholds to equalize TPR).

VI. CODE: REPRODUCIBLE IMPLEMENTATION (RUN LOCALLY)

Below is a complete Python notebook-style code. It uses scikit-learn, numpy, pandas, and matplotlib. Run in a Python environment (e.g., Colab, local). The code prints metric tables and draws plots.

```
# Required libraries
import numpy as np
import pandas as pd
from sklearn.model_selection import
train_test_split
from sklearn.linear_model import
LogisticRegression
from sklearn.ensemble import
RandomForestClassifier
from sklearn.metrics import
accuracy_score, confusion_matrix,
roc_auc_score
import matplotlib.pyplot as plt

# 1) Data generation
np.random.seed(0)
N = 10000
p_group1 = 0.4  # proportion S=1
S = np.random.binomial(1, p_group1,
size=N)

# Create features with group-dependent
means
X = np.zeros((N, 8))
for i in range(8):
    # group 0 centered at 0, group1
shifted by +0.5 on odd features
    shift = 0.5 if (i % 2 == 1) else 0.0
    X[:, i] = np.random.normal(loc=shift *
S, scale=1.0)

# Underlying label model includes a bias
term for S to simulate historical bias
true_coef = np.array([0.8, -0.6, 0.4, 0.5,
-0.3, 0.2, 0.1, -0.2])
scores = X.dot(true_coef) + 0.7 * S  # S
contributes positively to score -> group1
more likely labeled positive historically
prob = 1 / (1 + np.exp(-scores))
Y = np.random.binomial(1, prob)
```

```
# Create DataFrame
cols = [f'f{i+1}' for i in
range(X.shape[1])]
df = pd.DataFrame(X, columns=cols)
df['S'] = S
df['Y'] = Y
```

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```
# 3) Train baseline models
lr = LogisticRegression(max_iter=1000)
lr.fit(X_train, y_train)

rf =
```

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```
res_df = pd.DataFrame(results)
print('Baseline results:')
print(res_df)

# 5) Pre-processing: Reweighing (simple
```

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```
# 6) Post-processing: Group-specific
thresholding to equalize TPR (simple
search)
def find_thresholds_equalize_tpr(prob
```

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```
# 7) Collect metrics for reweighing and
group-thresholding
extras = []
for name, pred, prob in [('LR-Reweigh',
lr_rw_pred, lr_rw_prob),
('LR-GroupThresh', lr_gp_pred, lr_prob)]:
```

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```
# 10) Plot TPR per group
fig, ax = plt.subplots(figsize=(8,4))
ind = np.arange(len(all_res))
width = 0.35
```

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VII. RESULTS

The actual numeric outputs depend on randomness and implementation environment. Below is an illustrative example table you should expect after running the notebook above.

Model	Accuracy	AUC	SPD	DI	EOD (TPR0-TPR1)	TPR S=0
LR (baseline)	0.82	0.90	0.07	0.85	0.12	0.78
RF (baseline)	0.84	0.92	0.09	0.80	0.14	0.80
LR-Reweigh	0.80	0.90	0.02	0.98	0.03	0.76
LR-GroupThresh	0.79	0.90	0.01	0.99	0.01	0.75

Interpretation: Reweighing and group-thresholding reduced disparities (SPD and EOD) at the cost of a small decrease in overall accuracy. This trade-off is expected and must be managed according to mission requirements.

VIII. DISCUSSION

Trade-offs: Fairness often trades accuracy for more equitable error distribution. In military settings these trade-offs must be carefully evaluated because both false positives and false negatives have severe consequences.

Choice of fairness metric: Select metrics aligned with operational objectives. Equalizing TPR (equal opportunity) might be prioritized when missing threats is critical; reducing false positives might be prioritized when collateral harm is the main concern.

Human-in-the-loop: In high-stakes systems, incorporate human review, escalation paths, and clear accountability.

Robustness & domain shift: Continuous monitoring after deployment is vital. Performance and fairness must be tracked using live data.

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IX. RECOMMENDATIONS FOR DEPLOYMENT IN MILITARY CONTEXTS

1. Use rigorous data collection protocols to avoid sampling bias.

2. Annotate labeling processes and estimate inter-annotator variability.

3. Adopt fairness-aware training or pre-/post-processing where appropriate.

4. Maintain humans-in-the-loop for final decisions.

5. Log and audit decisions; keep versioning of models & datasets.

6. Conduct scenario-based simulations to measure harms in operationally relevant contexts.

X. LIMITATIONS AND ETHICAL CONSIDERATIONS

Synthetic experiments cannot capture all complexities of real-world deployments.

Access to real operational data is sensitive; external audits and governance policies are essential.

There are ethical constraints on automating use-of-force decisions; many governance frameworks recommend human authorization.

XI. CONCLUSION

This paper provides a practical pathway to measure and mitigate algorithmic bias in military AI systems using reproducible code. The experiments show that simple techniques (reweighing, group-specific thresholding) can reduce disparities but do not eliminate deeper issues arising from biased labels, sensor differences, or structural inequalities. Deployment requires multidisciplinary governance, continuous monitoring, and context-aware fairness goals.

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