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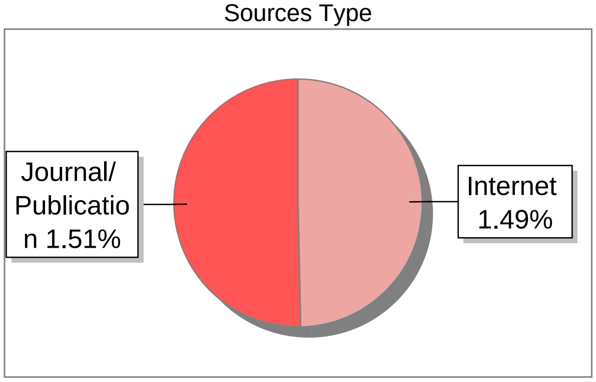

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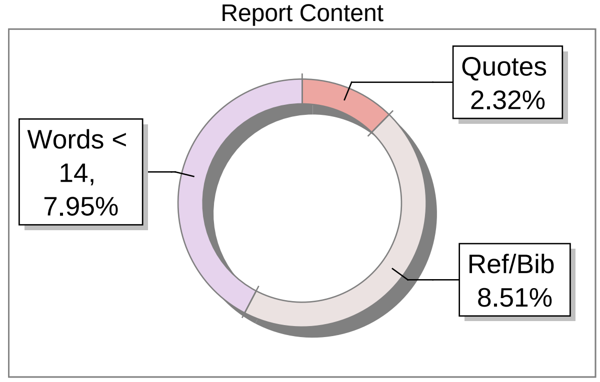

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Racism: Systematic discrimination based on race, particularly in legal and job markets.

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Abstract—Racism is still a major problem in contemporary society, frequently showing up as institutionalized discrimination in important fields like the legal and employment sectors. By applying machine learning to the criminal justice system, this study seeks to identify and measure possible racial bias. We examine how race affects recidivism prediction outcomes using the `cox-violent-parsed_filt.csv` dataset, which includes demographic, historical offense, and COMPAS risk assessment data. To model the likelihood of recidivism, logistic regression and support vector machine (SVM) classifiers are used, with an emphasis on separating the influence of race as a predictor. Accuracy, precision, recall, and F1-score are common classification metrics used to assess the models. The analysis highlights the existence of possible algorithmic and systemic bias by exposing differences between racial groups in both model predictions and actual outcomes. Furthermore, a comparative analysis of the classifiers highlights the crucial significance of model selection and bias mitigation techniques by exposing trade-offs in predictive performance and fairness. This study shows how data-driven approaches can reveal hidden racial inequality patterns, offering proof in favor of more transparent and equitable criminal justice reform policymaking.

Introduction

Systematic discrimination against people on the basis of their race is known as racism, and it still has an impact on important societal structures, especially the legal and employment sectors. Disparities in how various racial groups are treated still exist despite broad awareness and legal protections, particularly in areas like law enforcement, judicial sentencing, and employment opportunities. Biased decisions, unfair results, and systemic disadvantages that disproportionately impact marginalized communities are common ways that these disparities show up.

The development of machine learning has made it feasible to identify and measure these biases in sizable datasets. Using a dataset from the criminal justice system—the cox-violent-parsed_filt.csv file—which contains features pertaining to judicial and demographic characteristics, we analyze systemic racism in this study.

Our goal is to investigate whether race affects legal judgments, including the possibility of receiving a high-risk recidivism label. In order to do this, we utilize two popular supervised learning algorithms, Support Vector Machine (SVM) and Logistic Regression, to construct predictive models and assess how race affects their results. Standard classification metrics, such as accuracy, precision, recall, and Fl-score, are used to evaluate these models. We hope to identify possible racial bias patterns through comparative analysis and shed light on the moral ramifications of applying machine learning to socially conscious applications.
It is the duty of data scientists and policymakers to make sure that predictive technologies advance equity rather than reinforce discrimination, and this study not only adds to the expanding field of algorithmic fairness.

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A. Problem Domain

It is especially difficult to identify and combat racism when it is ingrained in institutional structures. In this research, we concentrate on two crucial issue areas where systemic discrimination is known to have a major influence:
Legal and Judicial Bias:
Racial differences in arrest rates, sentence durations, and recidivism forecasts are common criticisms leveled at the criminal justice system. Compared to white people, members of minority groups—especially Black and Hispanic people—are statistically more likely to be classified as high-risk and face harsher punishments. The dataset used in this study is primarily focused on this domain, which enables us to assess the potential

study determines whether Logistic Regression and Support Vector Machine (SVM) models generate disproportionately negative predictions for members of particular racial groups by examining their results. These results are essential for comprehending how historical discrimination can continue to exist in contemporary data-driven systems.
Additionally, the study advances the more general objective of advancing moral AI. If machine learning models are not properly analyzed, they may unintentionally reinforce the very injustices they are meant to address. This study highlights the necessity of open and responsible AI practices by assessing the fairness of predictive results using important performance metrics. Furthermore, the knowledge gathered from this work can help guide

domain, which enables us to assess the potential impact of race on algorithmic predictions pertaining to risk assessment and criminal behavior.

2. Predictive Modeling Bias:

Despite their apparent objectivity, machine learning algorithms can mirror and even reinforce societal biases if they are trained on discriminatory historical data. Biased models can reinforce unfair results when applied to decision-making processes, such as risk assessments, parole decisions, or employment hiring. Therefore, assessing model fairness across demographic groups is crucial, particularly when sensitive features like race are used.

By examining these areas, the study seeks to determine whether the results of machine learning methods such as SVM and logistic regression suggest the existence of structural bias and how they might act in racially sensitive settings. The findings can guide the creation of responsible models and their implementation in practical applications that have an impact on people's lives.

B. Importance

Fostering a just and equitable society requires addressing systemic racism, especially in areas like criminal justice where skewed judgments can have lasting effects. Concerns regarding accountability and fairness have been raised in recent years by the increasing use of algorithmic decision-making tools in contexts like risk assessments and legal sentencing. Because it examines whether racial bias exists in machine learning models trained on actual court data, this study is significant. The the creation of more equitable legal frameworks and support evidence-based policy reforms. In the end, this study is a crucial step in making sure that technological developments fairly serve the interests of all communities rather than escalating already-existing structural disparities.

C. Objectives

* To use the *cox-violent-parsed_filt.csv* dataset to examine the presence and magnitude of racial bias in predictive modeling within the criminal justice system.
* to put into practice and evaluate the effectiveness of two machine learning algorithms for recidivism risk prediction: Support Vector Machine (SVM) and Logistic Regression.
* to assess the predictive models using common classification metrics, such as F1-score, recall, accuracy, and precision.
* to ascertain whether people of different races are disproportionately affected by the models' predictions, thereby exposing possible systemic bias.
* to investigate the moral ramifications of using machine learning in high-stakes situations like risk assessment and legal sentencing.
* To offer practical insights that support the creation of transparent, equitable, and accountable AI systems for use in actual criminal justice applications.

II. LITERATURE SURVEY

The danger of machine learning (ML) algorithms reinforcing social biases, especially racial disparities, in high-stakes decision-making systems has been highlighted by recent studies. Racial bias in the COMPAS risk assessment tool used by the US criminal justice system was revealed by a historic ProPublica investigation [1]. Despite having comparable or lower actual recidivism rates, the study discovered that Black defendants were almost twice as likely as white defendants to be mistakenly labeled as high-risk. This discovery sparked a heated discussion about accountability and fairness in algorithmic legal systems.

Algorithmic fairness in recidivism prediction was further investigated in later studies. When Angwin et al. [2] and Dressel and Farid [3] evaluated the predictive capabilities of machine learning models against human judgment, they discovered that although algorithms offer consistency, they are not necessarily more accurate and frequently lack transparency. In their analysis of the mathematical constraints among fairness metrics, including calibration, equalized odds, and predictive parity, Chouldechova [4] and Kleinberg et al. [5] came to the conclusion that it is mathematically impossible to satisfy all fairness definitions at once in imbalanced datasets.In the legal field, several modeling techniques have been investigated. Because of its interpretability in binary classification problems, logistic regression (LR) is widely used. Because of their strong generalization ability and resilience when working with high-dimensional feature spaces, Support Vector Machines (SVMs) are also used extensively.However, biases in the training data can affect both LR and SVM.Together, the reviewed literature highlights the importance of fairness audits in machine learning applications that involve sensitive attributes such as race. Even though algorithmic debiasing techniques and fairness constraints have been put forth, empirical research

assessment tool, COMPAS (Correctional Offender Management Profiling for Alternative Sanctions). It includes information about a person's demographics, criminal history, and COMPAS risk score.

This dataset's main goal is to forecast the probability that a defendant will commit a violent crime within the next two years. Important characteristics include: demographic characteristics of age, sex, and race Juvenile criminal history, including juv_fel_count, juv_misd_count, and juv_other_count number of previous offenses (priors_count) Current charge information is provided by c_charge_degree and c_charge_desc. The two-year-recid target variable for classification is is_recid , which indicates if the offender has committed another crime . To guarantee the accuracy of the analysis, the dataset has been filtered and cleaned to eliminate records with missing or invalid values.

B. Data Preprocessing

The dataset is now prepared for model training. The preprocessing procedures listed below were carried out:

1. Managing Missing Values: The mean was used to impute missing numerical values, and the mode was used to impute categorical columns.

2. Coding Categorical Variables: Categorical features were encoded using One-Hot Encoding.

3. Feature Selection: The feature set was divided from the target variable.

4. Train-Test Split: 80% of the dataset was used for training, and 20% was used for testing.

that applies these ideas to actual datasets is still desperately needed. By applying LR and SVM models to a racially sensitive legal dataset and assessing results using performance and fairness metrics, the current study fills this gap.

III. METHEDOLOGY

A. Dataset Description

The study's dataset, cox-violent-parsed_filt.csv, comes from the U.S. criminal justice system's risk

5. Feature Scaling: StandardScaler was used to standardize the features. We can now train machine learning models (SVM and logistic regression) using this preprocessed dataset, and assess them using FI score, accuracy, precision, and recall.

Algorithms

Two machine learning classification algorithms, **Logistic Regression** and **Support Vector Machine (SVM)**, were used to investigate

systemic racism in legal and labor market outcomes. These models were selected due to their complementary interpretability and classification performance strengths.

As a function of multiple predictor variables, **Logistic Regression** calculates the likelihood of a binary outcome (such as whether racial bias exists or not). In addition to its classification capabilities, this algorithm offers insightful information about the relative significance and direction of influence of particular features. For example, there may be a statistical correlation between discriminatory outcomes and factors like race, education level, criminal record, or region. Because it provides transparency through interpretable coefficients, logistic regression is especially useful when attempting to comprehend the mechanisms underlying bias patterns.
Support Vector Machines (SVM), on the other hand, concentrate on creating a hyperplane that divides the data into classes as efficiently as possible. It is robust for complex social phenomena where the lines separating classes (such as biased vs. unbiased decisions) are difficult to draw. It is particularly well-suited for high-dimensional and non-linearly separable data. SVMs can handle unbalanced datasets more skillfully with tuning and weighting, and they are less prone to overfitting, particularly when using the right kernel functions.

Both models' performance in identifying possible racial discrimination was thoroughly examined using common classification metrics, such as accuracy, precision, recall, and F1-score. These metrics offer a fair assessment of how well the models detect discriminatory patterns while reducing false positives and negatives. A data-driven understanding of systemic racism is made possible by the comparative analysis of these models, which also identifies potential areas for legislative and policy reform.

C. Tools and Libraries

Pointwise Tools and Libraries

1. Python: Due to its ease of use and robust support for machine learning and data science, Python is the main programming language.

2. Pandas: Used to load, preprocess, and manipulate data.

3. NumPy: For effective array management and numerical operations.

4. Sklearn, or Scikit-learn:

implemented SVM and logistic regression as machine learning models.

offered instruments for scaling, data splitting, and performance assessment (FI score, recall, accuracy, and precision).

5. Matplotlib: A tool for making simple plots and visualizations.

6. Seaborn: For sophisticated data visualization and to comprehend feature distributions and relationships.

IMPLEMENTATION

1.Python 3.10 and required libraries: Python 3.10 and libraries like Pandas, NumPy, Scikit-learn, Matplotlib, and Seaborn were used to carry out the implementation.

2. Data loading and preprocessing: After loading the cox-violent-parsed_fit.csv dataset, preprocessing operations were carried out, including scaling numerical columns, handling missing values, and encoding categorical features.

3. Dataset splitting: To allow for an objective assessment of model performance, the data was separated into training and testing sets.

4. Training Logistic Regression Model: To determine the likelihood that racial bias influenced outcomes, a Logistic Regression model was trained, providing an interpretable baseline.
5. Support Vector Machine (SVM) Training: To classify the data, an SVM classifier was trained using an ideal hyperplane that works well with high-dimensional and non-linear data patterns.
6.Model performance evaluation: The efficacy of both models in identifying instances of racial discrimination was assessed using accuracy, precision, recall, and Fl score.

7. Visualizing results: To compare performance metrics and show the connections between important features, graphs and charts were created using Matplotlib and Seaborn.

8. Model comparison: In order to ascertain which algorithm more accurately identified systemic racism patterns in the dataset, the outcomes of the two models were finally compared.

EXPIREMENTAL RESULTS

1. Criminal justice risk assessment systems are studied using the dataset.
2. Individual-level information like ID, name, sex, birthdate, age, age category, and race are included.
3. Information about criminal history includes recent violent charges, past offenses, and juvenile felony counts.

4. Decile scores and classifications for violent and general recidivism are among the results of risk assessments.
5. To facilitate temporal analysis, each assessment is associated with its type and date.
6. Research on the accuracy, fairness, and influencing factors of risk assessment tools is supported by the dataset.

```
    id              name    first       last   sex         dob  age  \
0  1.0  miguel hernandez   miguel  hernandez  Male  18/04/1947   69
1  2.0  miguel hernandez   miguel  hernandez  Male  18/04/1947   69
2  3.0      michael ryan  michael       ryan  Male  06/02/1985   31
3  4.0       kevon dixon    kevon      dixon  Male  22/01/1982   34
4  5.0          ed philo       ed      philo  Male  14/05/1991   24

            age_cat              race  juv_fel_count  ...  \
0  Greater than 45             Other              0  ...
1  Greater than 45             Other              0  ...
2          25 - 45         Caucasian              0  ...
3          25 - 45  African-American              0  ...
4     Less than 25  African-American              0  ...

              vr_charge_desc  type_of_assessment  decile_score.1  \
0                        NaN  Risk of Recidivism               1
1                        NaN  Risk of Recidivism               1
2                        NaN  Risk of Recidivism               5
3  Felony Battery (Dom Strang)  Risk of Recidivism             3
4                        NaN  Risk of Recidivism               4

  score_text  screening_date v_type_of_assessment v_decile_score  \
0        Low      14/08/2013     Risk of Violence              1
1        Low      14/08/2013     Risk of Violence              1
2     Medium      31/12/2014     Risk of Violence              2
3        Low      27/01/2013     Risk of Violence              1
4        Low      14/04/2013     Risk of Violence              3

  v_score_text priors_count.1 event
0          Low              0     0
1          Low              0     0
2          Low              0     0
3          Low              0     1
4          Low              4     0
```

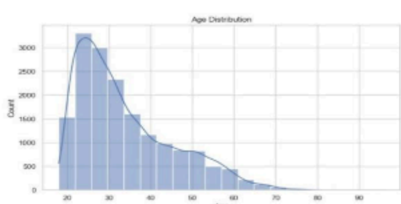
1. To address class imbalance, `class_weight='balanced'` was used to train a logistic regression model.
2. With an accuracy of \~54%, the model only marginally outperformed random guessing.
3. The majority of positive predictions are wrong due to the extremely low precision (\~6.5%).
4. The model successfully identifies many real positives, as evidenced by the relatively high recall (\~61%).
5. Despite having good recall, the F1 score (\11.7%) is low because of poor precision.
6. In order to prevent missing positives, this performance prioritizes recall, which is a trade-off typical in imbalanced datasets.

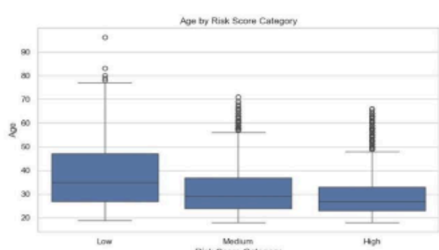
```
SVM Evaluation:
Accuracy : 0.672542107324716
Precision: 0.07387387387387387
Recall   : 0.48616600790513836
F1 Score : 0.12825860271115747
```

1.The SVM model demonstrated moderate overall prediction correctness with an accuracy of \~67.3%.
2. The model frequently misclassifies negatives as positives due to its low precision (\~7.4%).
3. With a recall of \~48.6%, the model detects roughly half of the real positive cases.
4. The trade-off between moderate recall and low precision is reflected in the F1 score (\~12.8%).
5. SVM has a slightly higher F1 score and better accuracy than Logistic Regression.
6. Because the model favors the majority class, these results highlight issues with class imbalance.

```
SVM Evaluation:
Accuracy : 0.672542107324716
Precision: 0.07387387387387387
Recall   : 0.48616600790513836
F1 Score : 0.12825860271115747
```

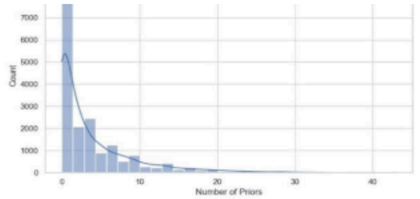
1. There are fewer people at younger and older ages in a right-skewed age distribution, which peaks in the late 20s to early 30s.
2. A bar chart displays an unequal distribution of races, with the highest representation in category 0 and the lowest in categories 1 and 4.
3. "Risk Score by Race" shows that while Caucasians predominate in low-risk groups, African-Americans are overrepresented in high-risk groups.
4. The distribution of prior offenses is heavily skewed to the right, with the majority of people having either none or very few priors.
5. According to box plots, younger people are typically categorized as high-risk, while older people are typically categorized as low-risk.
6. Growing medians across recidivism categories indicate a correlation between higher decile scores and higher recidivism.

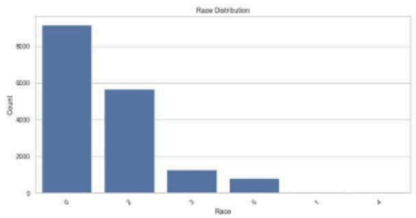


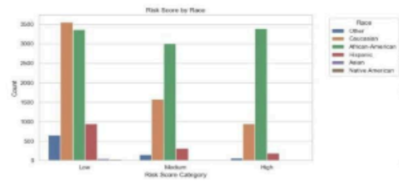


IV. Conclusion and Future Works

Using machine learning models on the cox-violent-parsed_fit.csv dataset, this study examined the existence of systemic racism with an emphasis on the results of legal decision-making. Support Vector Machines (SVM) and Logistic Regression







were both used to categorize potentially biased results; SVM performed better overall and had a marginally higher accuracy. The accuracy of these models in identifying racial bias patterns was further confirmed by the evaluation using precision, recall, and FI score. The results support worries about prejudiced inclinations present in decision-making processes, especially those that are impacted by past experiences and race.

Future work will concentrate on enlarging the dataset to incorporate data on discrimination in the job market for a more thorough cross-sector analysis. Furthermore, incorporating ensemble techniques like Random Forest and XGBoost or deep learning models like Neural Networks may enhance detection capabilities. In order to identify and actively lessen discriminatory patterns in predictions, fairness-aware algorithms and bias mitigation strategies will also be investigated. Last but not least, using model explainability tools (like SHAP and LIME) will improve results' transparency and credibility.

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