Challenges of Profiling Offenders for Recidivism Risk

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INNOVATIVE PRISON SYSTEMS

Introduction

Recidivism rate from 40% to 60% within two years [1].

For criminologists and societal stakeholders, curtailing recidivism rates remains paramount.

Officially documented criminal justice data contributes to partial insights into offender behaviour and crime trends.

Predictions faces limitation pinpointing the factors under-pinning recidivism and devising efficacious countermeasures.

Most ML methodologies for predicting recidivism risk are focused on optimal-performing techniques [2].

Strong association between demographic risk factors such as age, sex, ethnicity, and race [3].

We aim to find the best method highlighting the false positive (FP) rate.

Based on gender, data is divided into types of crime to compare with the whole dataset to determine if a unique scenario exists for a particular crime group.

Related Work

Tollenar et al. [4] explore the best approach using contemporary statistical methods, machine learning, and classical paradigms. Good results for general and violent recidivism but inconsistent sexual recidivism.

Another study [5] found that algorithms outperform human evaluators when enriched risk factor information is included in the prediction process.

Authors of [6] argue that commonly used COMPAS, does not perform as well in accuracy or fairness compared to those with limited or no prior experience in criminal justice.

The research [7] emphasizes the need for training machine learning models for specific geographical locations and regularly updating them over time.

In [8], the research aims to reduce youth recidivism through offender rehabilitation, using predictive modelling with statistical learning to surpass limitations faced by probation officers

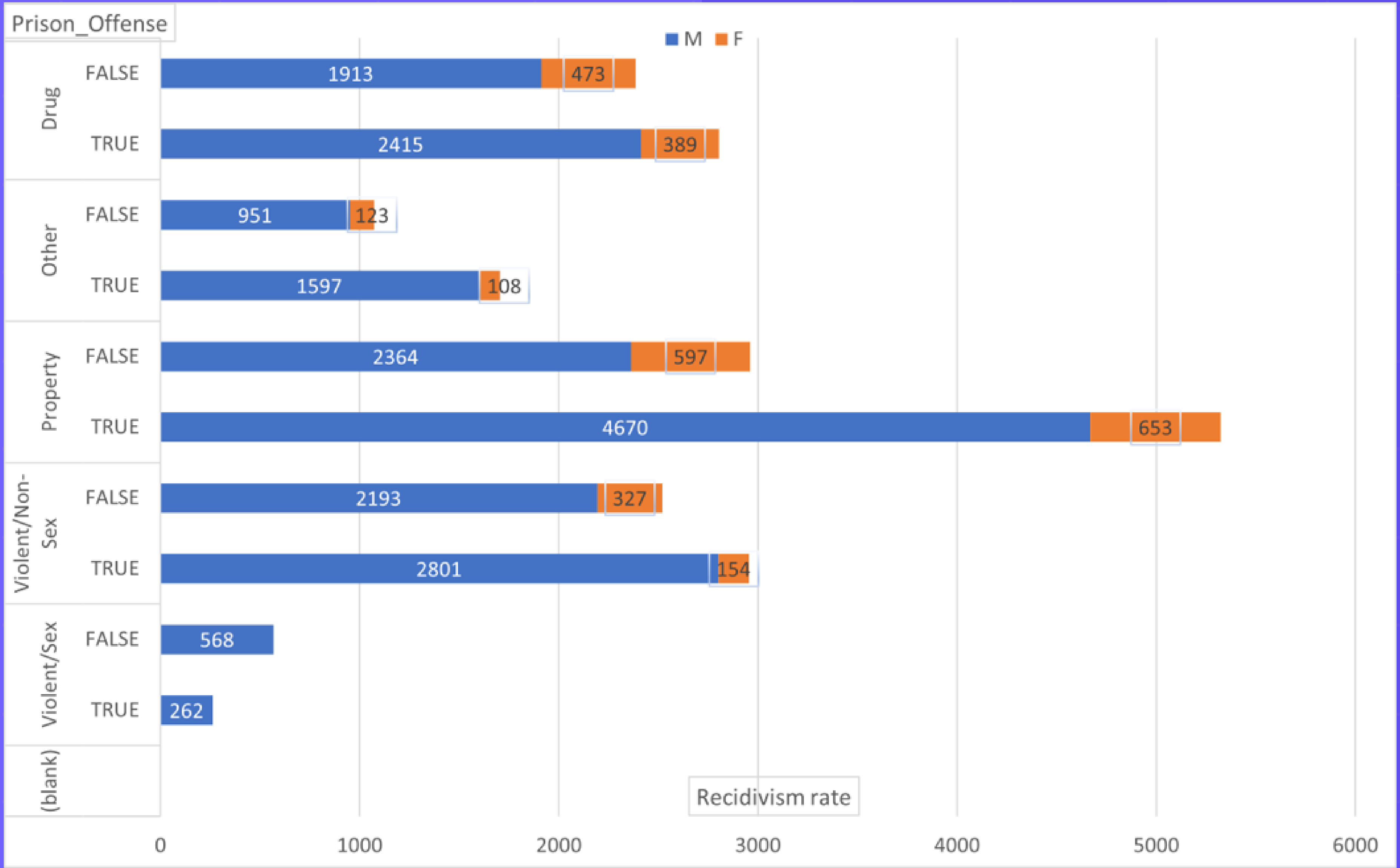
Recidivism Related Datasets

Dataset	Entries	Variables	Recidivism Rate
NIJ	25,835	54	57%
CEJFE	4,753	130	30-35%
COMPAS	7,214	53	45%

Methodology

- **Dataset:** NIJ challenge dataset provided by the US Department of Justice.
- Data on a gender is highly disproportionate.
- Crime categories: Property accounts for 36.62%; Violent/Non-Sex 24.27%; Drug 23.01%; other 12.32%; and Violent/Sex 3.68%.
- **Algorithms:** AdaBoost, Logistic Regression, Random Forest, Gaussian Naive Bayes, Decision Tree, Support Vector Machines, LightGBM, and XGBoost. (total:8)
- **Experiment:** Complete dataset, Gender-based for all crimes, Gender/based for each crime
- **Comparison:** Accuracy, Area Under the Curve (AUC), Recall, Precision, and F1 score.
- **Feature selection techniques:** Lasso Regression and two popular Chi-Square and Mutual information (MI).

Summary of Prison Offense for each Gender and Recidivism rates.



RESULTS: COMPLETE, MALE AND FEMALE DATA FROM THE ORIGINAL DATA

Dataset	AUC	Acc	FP	MIF	Model
C-Dataset	68	69	20	Residence PUMA	LGBM
Men-C	68	69	21	Residence PUMA	LGBM
Drug	66	66	20	Age Release 48/older	SVM
Property	66	69	24	Age Release 18-22	LR
Violent N/Sex	70	71	18	Age Release 18-22	LR
Violent Sex	72	76	8	MoveWithoutPermis.	LR
Others	64	67	21	Residence PUMA	AdB
Women-C	70	71	14	Age Release 18-22	LR
Drug	65	65	16	Age Release 18-22	LR
Property	68	68	16	Age Release 18-22	LR
Violent N/Sex	73	78	6	Residence PUMA	RF
Others	59	59	14	Arrest episode misd.	SVM

RESULTS: AFTER APPLYING LASSO REGRESSION

Dataset	AUC	Acc	FP	MIF	Model
C-Dataset	68	69	21	Residence PUMA	LGBM
Men-C	67	68	21	Residence PUMA	AdB
Drug	65	66	21	Age Release 18-22	LR
Property	66	68	24	Residence PUMA	AdB
Violent N/Sex	70	70	19	Age Release 18-22	SVM
Violent Sex	73	77	7	Program Attendances	RF
Others	65	66	22	Residence PUMA	AdB
Women-C	70	70	14	Age Release 18-22	LR
Drug	65	65	16	Age Release 18-22	LR
Property	69	69	16	Age Release 18-22	LR
Violent N/Sex	73	79	10	Arrest Episode Felony	RF
Others	64	64	17	Prison Yr 3/+	LR

RESULTS: AFTER APPLYING MUTUAL INFORMATION

Dataset	AUC	Acc	FP-Rate-%	Model
Comp - Ds	68	68	20	LGBM
Men-Comp	67	68	22	Adaboost
M - Drug	64	65	21	Log Reg
M - Property	66	68	23	LGBM
M - Violent Non-Sex	69	70	18	Adaboost
M - Violent Sex	74	77	6	Log Reg
M - Others	63	66	22	AdaBoost
Women-Comp	69	69	13	Log Reg
W - Drug	64	65	15	Log Reg
W - Property	68	68	16	Log Reg
W - Violent Non-Sex	72	78	10	Random F
W - Others	61	61	15	SVM

RESULTS: AFTER APPLYING CHI-SQUARE

Dataset	AUC	Acc	FP-Rate-%	Model
Comp - Ds	68	68	20	LGBM
Men-Comp	67	68	22	Adaboost
M - Drug	64	65	21	Log Reg
M - Property	66	68	23	LGBM
M - Violent Non-Sex	69	70	18	Adaboost
M - Violent Sex	74	77	6	Log Reg
M - Others	63	66	22	AdaBoost
Women-Comp	69	69	13	Log Reg
W - Drug	64	65	15	Log Reg
W - Property	68	68	16	Log Reg
W - Violent Non-Sex	72	78	10	Random F
W - Others	61	61	15	SVM

Discussion

After 48 separate experiments using eight machine learning algorithms:

Logistic regression provides the best results in Accuracy for 25 experiments, AdaBoost 8 times, and LightGBM, Support Vector Machine, and Random Forest provide five times each.

Total of 58 features and 32 after applying feature selection methods, 12 distinctly obtained features are most important for model prediction.

“Age at Release 18-22” repeated 21 times, “Residence PUMA” 9 times, and “Prior Arrests Episodes Felony” 6 times for different machine learning models.

Three most important features contributing to recidivism are young age, area of residence, and prior arrests due to felonies.

Discussion

Feature Selection resulted in a reduction of feature size to almost half with little effect on Accuracy (2% decrease to a maximum of 11% increase)

Recall and F1 scores of the true recidivism class for males range between 70% to 89%.m Except for sexual violence category for males has a higher score for false recidivism class in terms of Precision (79%), Recall (90%), and F1 score(84%).

FP rate for males is between 18 to 25% for most categories except for the crime of sexual violence, which is comparatively lower (6-8%).

Overall, the FP rate is significantly lower in Females mostly (6-10%)

Conclusions:

- Experiments underscore the difficulties in profiling offenders for recidivism risk,
  higher positive reoffense rate, **subpar data**, and **Accuracy.**
- Feature selection methods can reduce feature dimensions with minimal impact on overall performance.
- Inconsistent data statistics among genders emphasize the necessity of addressing them separately.
- Logistic Regression emerges as the optimal model for Accuracy in most crime-specific data subsets while boosting models excel with diverse crime types.
- **Proposed** future research: involving amalgamated data from diverse sources and crime-specific data, enabling the location- agnostic computation of recidivism risk

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Thank you!

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