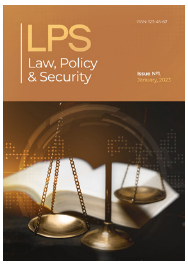

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Machine learning models for judicial information support

Abstract. The modern information society requires effective digital justice based on innovative technologies. This research aims to create machine-learning algorithms to evaluate the likelihood of prisoners reoffending, utilising their socio-demographic attributes and past criminal history. In this paper, the experimental method, modelling method, forecasting, field research, statistical analysis, case study, meta-analysis, comparative analysis, and machine learning techniques have been used. It was investigated that the main factors influencing the risk level (low, moderate, high) of recidivism are dynamic characteristics associated with previous criminal activities (court decisions for specific individuals provided for suspended sentences and early releases, rather than serving sentences in correctional institutions). The age at which a person was first involved in the criminal environment (first convicted to a suspended sentence or imprisonment for a certain period while serving in correctional institutions) also significantly affects the propensity for criminal relapse. Individual characteristics of convicts (age at the time of the study, gender, marital status, education level, place of residence, type of employment, motivation for release) are not correlated with a tendency to commit repeated crimes. The age at which a person was first sentenced to actual imprisonment or given their first suspended sentence, the age at which a person was first sentenced to the actual degree of punishment, the number of early dismissals, and the young age at which a person was first involved in the criminal environment (received their first suspended conviction or real conviction) are significant factors increasing the risk of committing

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a recidivist crime in the future. The proposed model can be applied to predict the level of propensity for recidivism crimes for new cases. The obtained results can provide reliable information support for court decisions and become part of a comprehensive court information system

Keywords: judiciary; predictive justice; legal support of the judiciary; court; artificial intelligence; decision-making; information systems

INTRODUCTION

Until recently, the potential for applying data science, artificial intelligence (AI), and machine learning (ML) to legal practice was seen as doubtful. Law involves so-called "human" tasks of critical analysis, analytical thinking, and logical reasoning. However, the use of new information technologies, especially ML, in the legal field is growing, opening up new possibilities for analysing large volumes of historical data, detecting non-obvious connections, and uncovering useful associations. AI systems can improve data quality and make justice systems more efficient. Modern jurisprudence requires effective analytics and forecasting tools to enhance legal analysis by examining vast datasets. Machine learning is being integrated more and more into judicial systems worldwide to support data-driven decision-making.

A growing number of researchers from different countries and leading international experts, particularly in the fields of information technology and cybersecurity, lawyers and judges, have been conducting new studies at the intersection of AI and law. Zh. Duan (2021) used an inter-jurisdictional and interdisciplinary approach to studying AI and law issues in a comparative context. P. Sarzaeim *et al.* (2023) conducted a systematic literature review on the application of ML methods in law enforcement. The authors examined the advantages and limitations of using these methods in smart policing to simplify understanding of the effectiveness of integrating machine learning into law enforcement practices. A. Tursunalieva *et al.* (2024) presented an overview of the main methods for interpreting AI models in the context of human-AI interaction and ensuring compliance with regulatory requirements. N.A.K. Rosili *et al.* (2021) presented a systematic review of studies on the application of machine learning methods to predict court decisions. K.M. Pilkov (2022) studied the benefits of integrating AI into the decision making process.

One important use of machine learning in legal systems is to enable "predictive justice", where algorithms analyse precedents to statistically forecast the outcomes of new cases. S. Yassine *et al.* (2023) explored the capabilities of using AI tools and assessed their impact on the efficiency of the judicial system. B. Mathis (2022) compared the effectiveness of using different machine learning algorithms for extracting relevant information from open court case data. By leveraging vast collections of case law and encoding it in a digestible form, the algorithms can statistically forecast the likely result of a given dispute through comparison to similar prior cases. D. Alghazzawi *et al.* (2022) applied a hybrid neural network model for efficiently predicting court decisions based on historical court data sets. E.Q. Nuranti *et al.* (2022) presented predictions on first instance court decisions using a collection of Indonesian court documents. Predicting legal case outcomes can support judicial decision-making. With recent advances in artificial intelligence, machine learning methods may serve as decision-support tools within the legal system. O.A. Alcántara Francia *et al.* (2022) analysed the effectiveness of different machine learning, deep learning and natural language processing methods for predicting judicial and administrative decisions. However, the potential downsides of utilising these technological tools must also be weighed. Careful oversight is needed to ensure fairness.

AI platforms offer various opportunities for improving justice systems. But Artificial intelligence systems do not replace human decision-makers. On the contrary, they can augment human decision-making and efficiency. S. Bhupatiraju *et al.* (2021) stated that AI provides informational support to human decision makers, but cannot replace them. Machine learning and artificial intelligence have immense potential to aid the legal system and court decisions by efficiently analysing massive amounts of data, and identifying patterns and connections that humans may miss. However, care must be taken to ensure these systems remain free of bias and generate fair outcomes. J. Zeleznikow (2023) explored the proper use of ML to support and generate legal predictions by examining proper data usage in global legal domains, including common law, civil law, and mixed jurisdictions.

AI/ML, data science, and law involve very different disciplines – Computer Science, Mathematics, Logic, Rhetoric, Psychology, and so on. Interdisciplinary will be key to successfully integrating these fields. Court decisions have high stakes, so AI/ML systems used in this context must undergo rigorous testing and monitoring. Transparency in system operations is vital for assessing fairness and engendering public trust. Overall, there is tremendous potential to leverage these technologies to enhance efficiency and justice in the legal system. However, care must be taken to weigh societal impacts and mitigate risks that could undermine core legal safeguards and values

The work aim was to study the possibilities of practical application of machine learning to assess the risk level of repeated offences by prisoners and provide information support for judicial decision-making. The resulting new knowledge and insights can provide the justice system with solid information to make relevant judicial decisions devoid of subjective judgements. The presented study employs a multidisciplinary approach to analysing the socio-behavioural characteristics of convicts and developing prognostic models based on them to calculate the probability of recidivism.

MATERIALS AND METHODS

The research presented in this paper provides reliable results on the extent (level) of such propensity based on the analysis of significant individual characteristics of persons convicted to imprisonment. This work presents the results of empirical studies conducted based on a dataset containing real data on 13,010 convicts sentenced to imprisonment in Ukraine. The input dataset contains information about the previous crimes of convicts and their social and personal characteristics (Table 1).

Table 1. Dataset description

Variable	Description	Value
RR	Recidivism rate	Nominal: low – crime levels lower than 2; moderate – crime levels between 3 and 4; high – crime levels higher than 4.
AGE	Age at the time of the study	Integer
AAP	Age at which a person was first sentenced to the actual degree of punishment	Nominal: 1 – age lower than 18; 2 – age between 18 and 30; 3 – age between 30 and 45; 4 – age higher than 45.
AAS	Age at which a person was first sentenced to actual imprisonment or given their first suspended sentence	Nominal: 1 – age lower than 18; 2 – age between 18 and 30; 3 – age between 30 and 45; 4 – age higher than 45.
ED	Number of early dismissals	Integer
SC	Number of suspended convictions	Integer
SEX	Sex	Binominal: 1 – male; 2 – female.
MS	Marital status	Nominal: 1 – single; 2 – married.
EL	Education level	0 – incomplete secondary; 1 – secondary; 2 – special secondary; 3 – incomplete higher, 4 – higher.
PR	Place of residence	Nominal: 1 – rural area; 2 – urban area.
TE	Type of employment	Nominal: 0 – unemployed; 1 – part-time; 2 –full-time.
MD	Motivation for dismissal	Nominal: 0 – no; 1 – yes.

Source: compiled by the authors

To determine the level of convicts' tendency to potentially commit repeated crimes in the future and identify the most significant factors (social and personal characteristics) influencing this level, authors built the following machine learning technique (Iorkaa *et al.*, 2021; Kamiri & Mariga, 2021):

- Naive Bayes;
- Generalised Linear Regression Model (GLM);
- Logistic Regression;
- Fast Large Margin;
- Deep Learning (DL) model;
- Decision Tree (TDs) model;
- Random Decision Trees (RDT) algorithm;
- Gradient Boosted Trees model (GBM).

A simple way to evaluate model performance is overall accuracy. This metric measures how accurately the model identifies convicts prone to recidivism. Accuracy is computed as the proportion of correctly classified samples (15 must-know machine learning..., 2021):

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}, \quad (1)$$

where *TP* – True Positives, *TN* – True Negatives, *FP* – False Positives, and *FN* – False Negatives.

Precision and recall are two key metrics for evaluating model performance. The first of them measures how accurate the model's positive predictions are, and the other measures what fraction of all positive cases the model correctly identified:

$$Precision = \frac{TP}{TP+FP}, \quad (2)$$

$$Recall = \frac{TP}{TP+FN}. \quad (3)$$

For a model to be acceptable, it needs both high precision (low false positives) and high recall (low false negatives). DL and GBM models have the highest accuracy (74%) (Fig. 1). For empirical studies, choose a Gradient Boosted Trees model (Gradient boosting..., 2024). Gradient boosting commonly uses decision trees, specifically Classification and Regression Trees (CARTs), of a fixed size as base learners. J.H. Friedman (2001) proposed a modification to the generic gradient boosting method that improves the fit of each base learner decision tree.

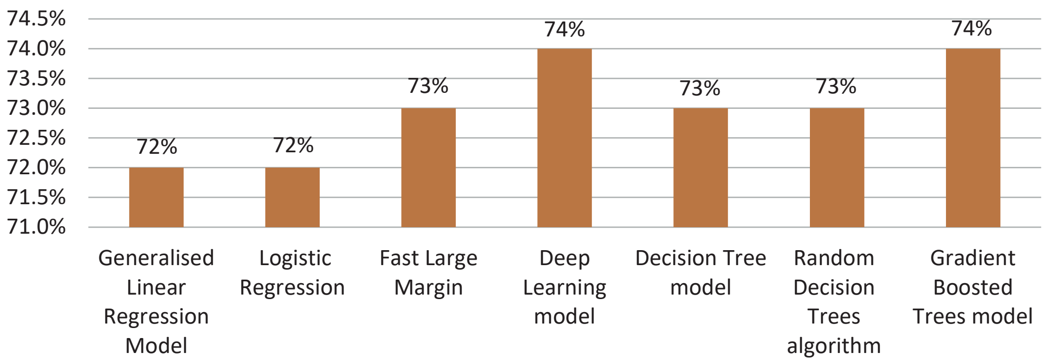

Figure 1. The accuracy of the built machine learning models
Source: compiled by the authors

In the generic gradient boosting approach, at step m a decision tree $h_m(x)$ is fitted to the pseudo-residuals. If J_m is the number of leaves of $h_m(x)$, then the tree partitions the input space into J_m disjoint regions $R_{1m}, R_{2m}, \ldots, R_{Jm}$, and predicts a constant value in each region. The output of $h_m(x)$ for input x can be written as:

$$h_m(x) = \sum_{I=1}^{Jm} b_{Jm} 1_{R_{Jm}}(x), \quad (4)$$

where b_{jm} – the predicted value in region R_{Jm}.
The coefficients b_{jm} are then multiplied by a value γ_m, chosen by line search to minimise the loss function. The model is updated as:

$$F_m(x) = F_{m-1}(x) + \gamma_m h_m(x), \quad (5)$$

$$\gamma_m = \underset{\gamma}{argmin} \sum_{i=1}^{n} L(y_i, F_{m-1}(x) + \gamma h_m(x_i)). \quad (6)$$

The modified algorithm "TreeBoost" is a choose a separate optimal γ_{im} for each of the tree's J regions, instead of one γ_m. The coefficients γ_{im} from tree-fitting can then be discarded. The model update rule becomes:

$$F_m(x) = F_{m-1}(x) \sum_{I=1}^{Jm} \gamma_{Jm} 1_{R_{Jm}}(x), \quad (7)$$

$$\gamma_m = \underset{\gamma}{argmin} \sum_{i=1}^{n} L(y_i, F_{m-1}(x_i) + \gamma). \quad (8)$$

A Gradient Boosted Trees model was built to predict the risk level of convicted criminals committing repeat offences in the future. The model was trained on criminal records and personal characteristics of 13,010 convicted individuals. The model development process consists of 5 steps. The process operators are presented in Figures 2-3. Table 2 presents the operators of the Gradient Boosted Trees model algorithm.

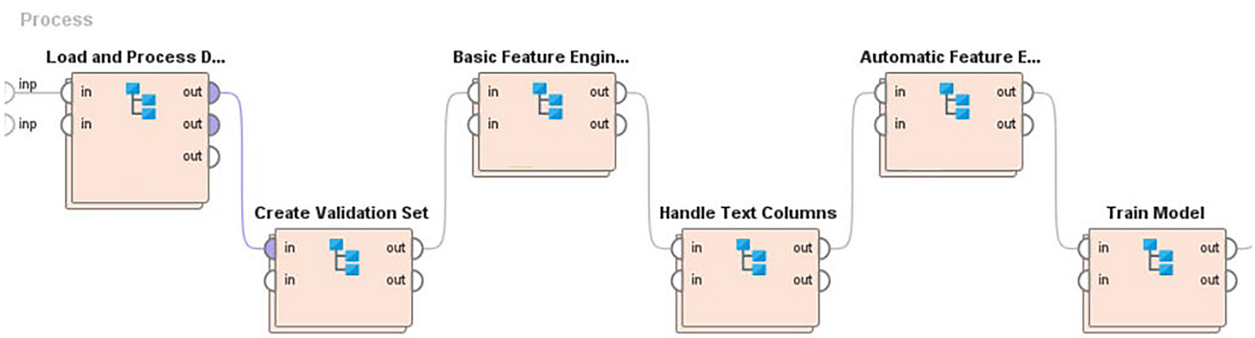

Figure 2. Process operators of the GBM model to predict the level of risk of recidivism (step 1-2)
Source: compiled by the authors

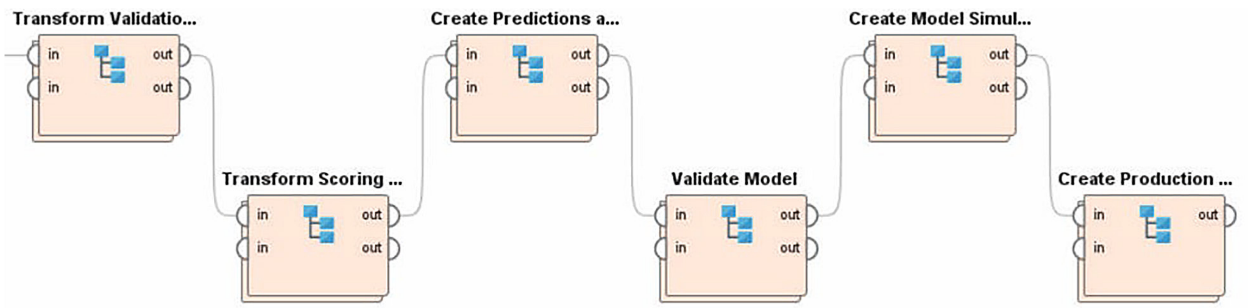

Figure 3. Process operators of the GBM model to predict the level of risk of recidivism (step 3-5)
Source: compiled by the authors

Table 2. GBM model process operates

No	Step	Operator	Description
1.	Basic Pre-processing	Load and Pre-process Data	The data set is loaded and basic pre-processing tasks are performed. Both labelled and unlabelled data points are provided – the unlabelled points will later be used for model application.
		Crete Validation Set	The data is split into training and validation sets, with the validation set to be used for robust performance evaluation across multiple hold-out fold.
		Basic Feature Engineering	Basic feature engineering and pre-processing steps are taken, like handling missing values and encoding categorical variables. Text columns will be processed separately at a later stage.
2.	Feature Engineering and Modelling	Handle Text Columns	Text columns are processed if needed and the text processing model is persisted.
		Automatic Feature Engineering	Automatic feature engineering is performed if desired, in addition to the basic pre-processing done earlier (text processing, date handling, encoding etc.).
		Train Model	The model is then trained, with automatic hyperparameter tuning (parameter optimisation) applied if wanted.
3.	Transform Validation and Scoring Data	Transform Validation Data	The validation data (with known target values) is transformed using the same pre-processing steps and feature engineering as the training data
		Transform Scoring Data	The scoring data (with unknown target values) is then pre-processed and engineered in the same way, to be consistent with the training and validation data.
4.	Scoring, Validation, Explanations, Weights and Simulator	Create Predictions and Explanations	The trained model is used to generate predictions and explanations on both the validation data and scoring data. Model-specific weights are also calculated during this scoring process.
		Validate Model	A robust validation approach using multiple hold-out sets is implemented, providing performance estimate quality comparable to cross-validation but with reduced computational runtime.
		Create Simulator Model	

Table 2. Continued

No	Step	Operator	Description
5.	Production Model	Create Production Model	The final production model is created by training a new model using the same parameters on the combined training and validation datasets.

Source: compiled by the authors

ML models can be very useful for predicting recidivism risk levels. They demonstrate high computational power and accuracy in predicting the likelihood of prisoners committing repeat offences.

RESULTS AND DISCUSSION

Out of the 13,010 convicted persons who comprised the initial dataset, 7,053 have a low propensity for repeat recidivism, 3,245 have a moderate propensity, and 2,713 are characterised as having a high propensity for repeat recidivism (Fig. 4). The SEX variable turned out to be insignificant, so it was not included in the predictive model. For the other variables, weights were calculated for Gradient Boosting Trees weights (Fig. 5).

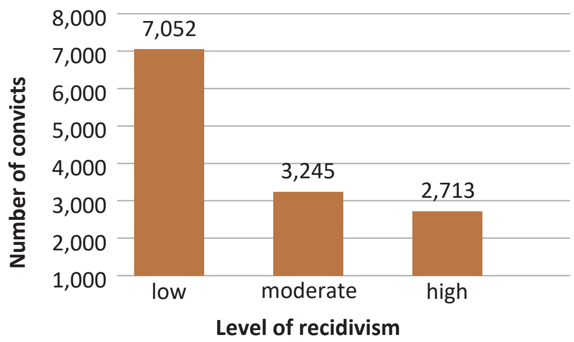

Figure 4. Distribution of convicted persons from the initial dataset into groups by level of propensity for recidivism

Source: compiled by the authors

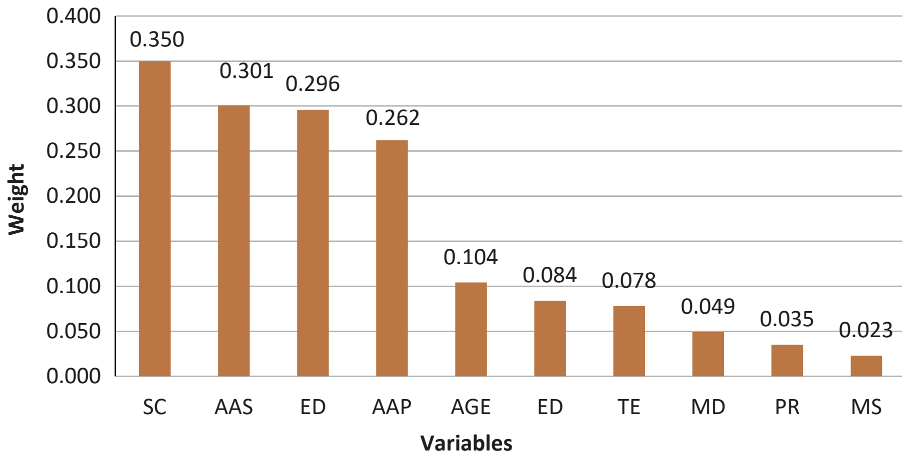

Figure 5. Gradient Boosting Trees weights

Source: compiled by the authors

The SC variable has the greatest weight in distributing convicts into groups according to their tendency to commit repeat offences (0.350). Therefore, the most significant characteristic of convicts associated with recidivism is the number of suspended convictions. The lack of real punishment for criminal activity creates the illusion of impunity and is the main reason that prompts offenders to commit new crimes. The second most important is the AAS variable (0.301). The age at which a person was first sentenced is also crucial for the distribution of convicts into groups (low, moderate, high) according to the risk level of committing repeat offences in the future. The earlier a person becomes involved in criminal activity, the more likely they are to commit recidivism. Next in importance is ED (0.296). Early dismissals are a significant factor correlated with repeat offending. Reducing the term of punishment is the cause of future recidivism. The AAP variable is the last in the top 4 characteristics of convicts that are most relevant to repeat offending. The age of the person when they are first convicted to serve a sentence in a penitentiary institution significantly affects their future criminal activity. The sooner they become integrated into the environment of professional criminals, the more likely they will be involved in criminal networks in the future. Indicators characterising the previous criminal activity of convicts have the greatest impact on the risk level of repeat offending. Individual statistical indicators such as a prisoner's actual age (weight = 0.104), education level (weight = 0.084), type of employment (weight = 0.078), motivation for dismissal (weight = 0.049), place of residence (weight = 0.035), marital status (weight = 0.023) have a significantly lower impact on the convicts' tendency towards recidivism. Therefore, penitentiary institutions do not perform a corrective function. On the contrary, in most cases, a person's integration into the criminal environment is the reason for their involvement in criminal activities in the future. Table 3 presents the bivariate correlations between the dependent variable and each of the independent variables.

Table 3. Correlations coefficients for all variable pairs

	AGE	AAP	AAS	ED	EL	MS	MD	PR	SC	TE
AAP	0.370									
AAS	0.343	0.869								
ED	0.146	-0.214	-0.228							
EL	0.079	0.179	0.181	-0.057						
MS	0.117	0.112	0.101	0.030	0.106					
MD	-0.010	0.056	0.046	0.019	0.084	0.117				
PR	-0.027	-0.049	-0.048	0.025	0.147	-0.006	0.040			
SC	-0.002	-0.129	-0.226	0.187	-0.048	-0.010	0.004	0.052		
TE	0.057	0.133	0.126	0.022	0.236	0.165	0.163	0.111	-0.063	
RR = low	-0.140	0.358	0.412	-0.404	0.115	0.028	0.066	-0.046	-0.474	0.107
RR = moderate	0.004	-0.157	-0.191	0.152	-0.062	0.003	-0.026	-0.000	0.086	-0.048

Source: compiled by the authors

The variables that correlate most with a low propensity for future recidivism are: SC (-0.474), AAS (0.412), ED (-0.404), and AAP (0.358), with inverse correlations observed between RR = low and SC, as well as between RR = low and ED. Therefore, the earlier dismissals and suspended convictions the convict had, the higher the likelihood that they will commit new crimes in the future. If a person is first brought into the criminal environment (receives their first suspended conviction or real conviction) at a younger age, the higher the risk that they will commit recidivism in the future. The variables that correlate most with a moderate propensity for repeat offences are: AAS (-0.191), AAP (-0.157), and ED (0.152). The inverse correlations for the AAS and AAP variables confirm that an individual's involvement in the criminal environment at a younger age is a significant factor in their propensity for repeat offences. Early dismissals give such criminals hope for reduced punishment for any future crimes they commit. Table 4 presents the high estimation of the precision and recall of created models.

Table 4. Variables correlation and repeat offenses precision-recall: Confusion Matrix

	true high	true moderate	true low	class precision
predicted high	487	167	31	71.09%
predicted moderate	184	426	133	57.34%
predicted low	116	335	1838	80.30%
class recall	61.88%	45.91%	91.81%	

Source: compiled by the authors

Precision and recall are sufficient. The model is acceptable. The Gradient Boosting Tree simulator predicted a low propensity for recidivism for 64% of prisoners from the initial dataset, a moderate level for 30%, and a high level for only 6% of convicts serving sentences in the penitentiary institutions of Ukraine (Fig. 6). Therefore, the criminal environment in Ukraine is characterised by a low level of repeat offences, despite the fact that the judicial system gives many prisoners chances for rehabilitation.

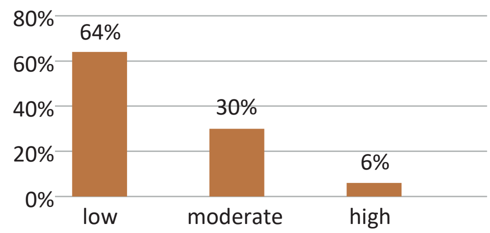

Figure 6. Predicted propensity of convicts to recidivism by levels (low, medium, and high)

Source: compiled by the authors

For each of the prisoners from the input dataset, the probability of predicted belonging to the groups (low, moderate, high) according to the propensity level for committing repeat offences in the future was determined (Table 5). Using the simulator of the constructed Gradient Boosting Tree Model, it is possible to determine with high probability the belonging to one of the recidivism levels (low, moderate, high) for each new case (Fig. 7).

Table 5. Predictions of the Gradient Boosting Tree (fragment)

Row No.	RR	Prediction (RR)	Confidence (high)	Confidence (moderate)	Confidence (low)	AAS	AAP	SC	ED
19	moderate	moderate	0.231	0.601	0.168	2	2	0	2
775	low	low	0.042	0.116	0.842	3	2	4	0
1,033	low	low	0.038	0.058	0.905	4	4	0	2
1,316	high	high	0.744	0.063	0.163	1	1	1	3
2,233	moderate	moderate	0.230	0.602	0.169	2	2	2	2
2,509	high	high	0.782	0.055	0.163	2	1	5	1
2,298	high	moderate	0.252	0.580	0.068	2	2	2	2
2,916	moderate	moderate	0.163	0.579	0.258	3	2	1	1
3,274	low	low	0.037	0.057	0.905	4	4	3	0
3,687	high	high	0.783	0.055	0.163	1	1	5	1
4,308	moderate	low	0.048	0.110	0.842	2	2	4	0
5,044	high	high	0.781	0.056	0.163	4	3	2	1

Source: compiled by the authors

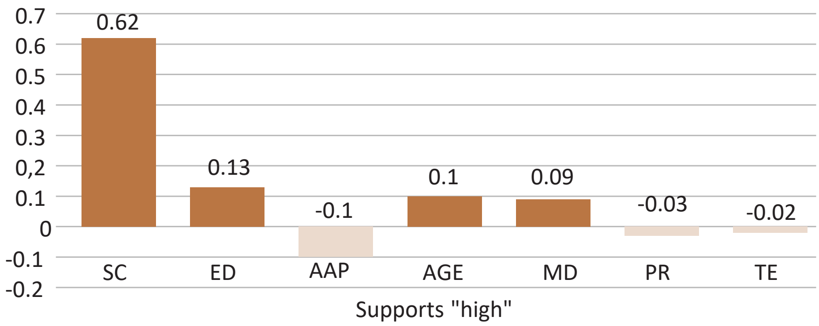

Figure 7. Important factors for recidivism level = "high"

Source: compiled by the authors

The most important factors for assigning individuals to the group with a high propensity for repeat offences are the number of suspended convictions (SC) and the number of early dismissals (ED). These factors identify convicts as "persistent recidivists". Also important is the age at which a person first goes to prison (AAP). At a young age, convicts are more susceptible to the influence of the criminal environment and realise their involvement in it. The influence of the AGE variable can be explained by the fact that a person acquires criminal experience throughout life, and recidivists are usually no longer young. An interesting fact turned out to be the influence of the MD (motivation for dismissal) variable on the high propensity for recidivism. This category of people already has experience with early dismissals and aims to return to the criminal environment. The insignificant influence of the variables PR (place of residence) and TE (type of employment) indicates that people living in an urban area and having a full-time job are less likely to become persistent recidivists. In this paper, a multidisciplinary perspective has been taken, drawing from machine learning algorithms and their application to predicting recidivism rates to contribute to the need for new approaches to evaluating the risks of parole, and probation, calculating optimal incarceration terms, and determining a defendant's level of danger to society. This article continued a series of studies from a multidisciplinary data science and machine learning perspective to build reliable information support for judicial decisions. In previous works of the authors, a factor model was built to identify consolidated factors that highlight substantive individual characteristics of criminals and increase the risk of repeated criminal offences. Machine learning models have been developed to identify factors (individual characteristics of prisoners) that have a significant impact on the propensity to commit criminal recidivism, according to O.Ya. Kovalchuk *et al.* (2023). An associative rule mining model has been built to extract non-obvious interdependencies between a historical crime data set of convicted and repeated offences. Correspondence analysis has been applied to identify relationships between criminal recidivism and elements of convicted persons' previous criminal histories. Earlier research focused on predicting the likelihood of convicted persons reoffending. For example, a logistic regression model was created that, by analysing real dynamic and statistical characteristics of convicts, provides relevant information for making effective post-trial decisions, as was noted by K.M. Berezka *et al.* (2022).

This work aimed to assess the risk level of reoffending, which is the risk of danger to society and is a mandatory criterion considered by the court when imposing a sentence. In the judiciary, making the right decisions is critical because people's freedom and lives depend on them. The modelling results must be reliable and indisputable. It is important to verify their reliability by applying several methods to the same data and comparing outcomes. The estimates obtained as a result of the analysis in this article confirm the results of the author's previous studies. The number of suspended convictions and early dismissals has the greatest impact on convicted persons' propensity to commit criminal recidivism. Offenders who have not served or fully served a term of actual punishment for previous crimes perceive the leniency of the judicial system not as a chance for correction but as a guarantee of impunity. The convicted person's age when sentenced to actual punishment or when a soft conditional sentence is imposed is also important. In adolescence, the personality is not yet formed, so there is a high probability of imitating the behaviour of a criminal environment and imitating criminal authorities.

The problem of choosing the best methods for predicting the risk of criminal recidivism remains relevant in scientific circles. However, it is difficult to develop a universal ML application approach that will be effective for different data sets with different attributes. Therefore, it is important to find the optimal ML model for each specific case. This statement is confirmed by the work of researchers M.M. Farayola *et al.* (2023). They used interpretable ML models to predict recidivism. The authors experimentally proved that ML models can be more accurate if trained separately for different data sets and constantly updated. In addition, there are regional differences in the sets of individual characteristics of a person that are used to assess the risk of recidivism. For example, skin colour is a significant characteristic for many countries engaged in developing such predictive models. G. Mohler and M.D. Porter (2021) proposed linear and gradient-boosting models to predict recidivism to reconcile performance metrics in black and white groups. Such studies are not relevant for examining the issue of recidivism in Ukraine, since in Ukraine the percentage of black people in the general population is low, and cases of their conviction are isolated incidents. S. Fazel and A.A. Wolf (2015) performed a comparative examination of numerous studies evaluating recidivism rates for reoffending across different nations and determined that cross-national data lacked comparability, as the sampling of crime data and definitions employed for recidivism exhibited substantial variability between countries.

The obtained in this paper results are only approximate estimates and require careful advanced analysis. However, they can provide reliable information support when making judicial decisions regarding the appropriateness of conditional punishment, early release, or the possibility of the defendant's participation in probation. In Ukraine, the application of data science, artificial intelligence, and machine learning to legal practice has not yet become widespread. The Ukrainian judicial system faces difficulties associated with processing huge amounts of data and transparency of the judicial system. The proposed machine learning model for determining the propensity of prisoners to commit future recidivism can become part of the information support of a unified information system to support judicial decision-making. As foreign experience shows, the mass integration of machine learning into judicial systems around the world contributes to improving the efficiency of supporting data-based judicial decisions, according to F.F. Vasconcelos *et al.* (2023) and P. Sarzaeim *et al.* (2023). In addition, it has been scientifically proven that the results of ongoing court cases are influenced by decisions made regarding previous, even unrelated court cases (Bhupatiraju *et al.*, 2021). P. Saravanan *et al.* (2021) explored the capabilities of analysing data from huge repositories, analysing various socioeconomic factors related to criminal events, and developing effective computational models for predicting crimes using data mining and ML methods. They conducted an analysis of recidivism rates on an international scale, however, they did not find obvious connections in the crime data sets with the level of re-incarceration. The authors explained such a result by significant differences in the legislation of different countries. For example, in some countries, a repeated conviction entails fines as a form of punishment.

W. Safat *et al.* (2021) studied the possibilities of improving the accuracy of crime prediction based on machine learning models. Unlike author's research, they predicted the risk of committing different types of crimes and forecasted the regions in the United States most threatened by the commission of future crimes. Scientists pay particular attention to assessing the probability of criminality and the risk of recidivism. This explains the fact that it is the criminal's personality, not the fact of the crime itself, that shapes this risk and is the subject of thorough study. As experience shows, the probability of committing repeated crimes significantly exceeds the probability of committing a primary crime J. Zhang (2023) applied ML algorithm models for assessing criminal recidivism risk. An offender who has already been convicted is exposed to a much greater risk of preconisation (adopting elements of the criminal subculture) and stigmatisation (following criminal traditions). These results correlate with the estimates obtained by the authors: the number of previous incarcerations increases the risk of committing a repeat offence. K.S. Anazodo *et al.* (2019) investigated the social stigmatisation of former prisoners' identities. Research reveals that having a prior conviction and history of incarceration influence an individual's self-perception as part of the criminal milieu. This finding further corroborates the conclusions drawn from author's study. The machine learning model presented in this work is developed based on a real dataset about convicts and can provide unique information for each specific case. This will reduce bias against convicts and existing "traditions" in making judicial decisions.

Modern Ukrainian jurisprudence requires effective analytical tools to improve legal analysis. Machine learning has enormous potential to increase the efficiency of the judicial system. Ukraine's justice system has already undergone digital transformation by introducing information technologies, in particular e-justice, into its activities, according to V. Teremetskyi *et al.* (2023). However, inconsistencies at the legislative and institutional levels, as well as resource constraints, do not yet make it possible to fully utilise data science, artificial intelligence, and machine learning tools to ensure reliable judicial information support.

The development of universal predictive models and the integration of machine learning into judicial systems around the world are increasing to improve data-driven judicial decision support. Ukraine's justice system is undergoing digital transformation and requires the implementation of new approaches to assessing the risks of parole/probation, calculating optimal incarceration terms, determining the convict's propensity for repeat offences, and the defendant's level of danger to society. Such information is taken into account when rendering judicial verdicts and can provide reliable information support to the judicial authorities.

CONCLUSIONS

The modern judicial system requires reliable information support based on innovative data science, machine learning and artificial intelligence tools. Particular attention should be paid to the problem of developing reliable models for predicting the level of criminal recidivism. Its solution is directly related to making effective judicial decisions that must balance adequate punishment of criminals with public safety. Research in this area must take into account the specifics of the criminal environment and the legislation of a particular country. In Ukraine, such developments are still in their infancy.

This paper presents the results of applying machine learning algorithms to predict the propensity of persons previously convicted of crimes to commit repeated offences. The model was trained on a unique dataset of 13,010 prisoners serving sentences in Ukraine's correctional institutions. The records about the convicts contain information about the prisoners' previous criminal activities (age at which a person was first sentenced to actual imprisonment to the actual degree of punishment, age at which a person was first sentenced to actual imprisonment or given their first suspended sentence, number of early dismissals, number of suspended convictions) and their characteristics (age at the time of the study, sex, marital status, education level, place of residence, type of employment, motivation for dismissal). An ensemble of ML models was developed and their effectiveness in predicting recidivism was compared. The Gradient Boosted Trees algorithm produced the most accurate model for classifying prisoners as having low, moderate, or high propensity for reoffending after release. The analysis found that past criminal activities, such as several suspended sentences and early releases, along with age at first conviction are the most predictive factors of recidivism risk. These dynamic characteristics outweighed individual demographic variables like gender, education level, and employment status. Lenient court decisions indirectly become a probable cause creating a false sense of impunity for criminals. The model achieved sufficiently high precision and recall, indicating its effectiveness for recidivism risk estimation. It predicted that 64% of prisoners have a low tendency for repeat offences, 30% moderate risk, and 6% high risk. The tool can assist courts by providing data-driven risk assessments to inform sentencing and parole decisions.

The obtained results are not absolute indisputable assessments but can provide significant information for making subsequent judicial decisions in similar cases. The developed Gradient Boosting Trees model can be used to predict the probable level of propensity for criminal recidivism separately for each new offender. This will provide reliable information support when making judicial decisions regarding the type of punishment, term of punishment, and the possibility of participating in probation for the convicted person. The potential for applying machine learning to improve judicial information support and the justice process itself is undeniable. However, information technology cannot replace decision-makers and will never become a panacea for the justice system. It only increases the objectivity of judicial decisions. The subject of further research will be the construction of an associative model of hot spots of crime based on data on previous crimes.

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CONFLICT OF INTEREST

None.

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Моделі машинного навчання для інформаційної підтримки судочинства

Анотація. Сучасне інформаційне суспільство вимагає ефективного цифрового правосуддя, заснованого на інноваційних технологіях. Метою цього дослідження було створення алгоритмів машинного навчання для оцінки ймовірності вчинення рецидиву злочинів ув'язненими, використовуючи їхні соціально-демографічні характеристики та минулу кримінальну історію. У цій роботі були використані експериментальний метод, метод моделювання, прогнозування, польові дослідження, статистичний аналіз, аналіз конкретних ситуацій, мета-аналіз, порівняльний аналіз та методи машинного навчання. Досліджено, що основними факторами, які впливають на рівень ризику (низький, помірний, високий) рецидиву, є динамічні характеристики, пов'язані з попередньою злочинною діяльністю (судові рішення щодо конкретних осіб передбачали умовне засудження та дострокове звільнення, а не відбування покарання у виправних установах). Вік, у якому особа вперше була залучена до кримінального середовища (вперше засуджена до умовного покарання або позбавлення волі на певний строк під час відбування покарання у виправних установах), також суттєво впливає на схильність до кримінального рецидиву. Індивідуальні характеристики засуджених (вік на момент дослідження, стать, сімейний стан, рівень освіти, місце проживання, вид зайнятості, мотивація звільнення) не корелюють зі схильністю до вчинення повторних злочинів. Вік, у якому особа вперше була засуджена до реального позбавлення волі або отримала перше умовне покарання, вік, у якому особа вперше була засуджена до реальної міри покарання, кількість дострокових звільнень, а також молодий вік, у якому особа вперше потрапила у кримінальне середовище (отримала перше умовне засудження або реальний вирок), є значущими факторами, що підвищують ризик вчинення рецидивного злочину в майбутньому. Запропонована модель може бути застосована для прогнозування рівня схильності до рецидивних злочинів за новими справами. Отримані результати можуть забезпечити надійну інформаційну підтримку судових рішень та стати частиною комплексної інформаційної системи суду

Ключові слова: судочинство; прогнозне правосуддя; правове забезпечення судової влади; суд, штучний інтелект; прийняття рішень; інформаційні системи