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Prediction Machine Learning Models on Propensity Convicts to Criminal Recidivism

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Abstract: Increasing internal state security requires an understanding of the factors that influence the commission of repetitive crimes (recidivism) since the crime is not caused by public danger but by the criminal person. Against the background of informatization of the information activities of law enforcement agencies, there is no doubt about the expediency of using artificial intelligence algorithms and blockchain technology to predict and prevent crimes. The prediction machine-learning models for identifying significant factors (individual characteristics of convicts), which affect the propensity to commit criminal recidivism, were applied in this article. For predicting the probability of propensity for criminal recidivism of customers of Ukrainian penitentiary institutions, a Decision Tree model was built to suggest the probability of repeated criminal offenses by convicts. It was established that the number of convictions to the actual punishment and suspended convictions is the main factors that determine the propensity of customers of penitentiary institutions to commit criminal recidivism in the future. Decision Tree models for the classification of convicts prone or not prone to recidivism were built. They can be used to predict new cases for decision-making support in criminal justice. In our further research, the possibility of using the technology of distributed registers/blockchain in predictive criminology will be analyzed.

Keywords: machine learning; blockchain technology; predicting; decision tree model; internal security; criminal recidivism; decision-making

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1. Introduction

The issue of security has become critical not only for development but also for the survival of modern smart society. The research on internal state security problems requires special attention. Forensics is one of the important components of ensuring the personal safety of citizens and national security in general. Modern society does not have full confidence in institutions of criminal justice. Hundreds of prisoners around the world are spending time in prison because of false charges. Innocent people are convicted on forged or false evidence and testimony causing social and economic discontent [1]. Law enforcement agencies are increasingly using AI and blockchain technology to transparently and securely collect, process, and access evidence. Artificial intelligence, big data, blockchain, the Internet of Things, digitization, and nanotechnology create an environment for new threats that will intensify in the future. In the coming years, new technology will become an important tool even in national security and criminal justice. Smart society is vulnerable to cyberattacks, so nowadays the world is recording an increase in the number of crimes that take place in cyberspace and significantly affect security. To uncover and prevent such crimes, law enforcement agencies must use information technologies focused on data mining and machine learning techniques [2–5]. This opens up wide opportunities for the implementation of new strategic approaches, i.e., smart policing. This consists of the rational use of data and knowledge, analytical methods, increasing efficiency, introducing innovations to reduce the level of crime, and increasing the relevance of the evidence base [6]. The analysis of crime consists not only of the disclosure of already committed crimes but also of the identification of non-obvious patterns and trends of crime in order to prevent the commission of future crimes, in particular, relapses. Law enforcement agencies are increasingly using the latest information technologies to fight and prevent crime, including biometrics, audio eavesdropping, and even virtual reality. One of the most controversial AI tools is the use of algorithm-based predictive policing to predict the location of a future crime [7,8]. One of the successful applications of AI in criminal justice is an artificial neural network that can identify criminals by specific facial features [9]. Information technology and analytical methods are effective tools for analyzing evidence and assessing its relevance to an investigation or trial in criminal justice. Thus, a technology-assisted review (TAR) is used to form an evidence base to support the adoption of a reasoned decision in criminal proceedings and to conduct analytics of pre-trial decisions. This is a range of machine-reading algorithms, including analysis and predictive coding for the classification of legal documents [10,11]. The use of machine learning algorithms to support decision-making in criminal justice can be extremely beneficial to the justice system in general. D. Zhdanov et al. present a systematic framework to build and evaluate AI systems that include principles of fairness, accountability, and transparency (FAT) [12].

Blockchain technology is a distributed database or electronic ledger under decentralized control, allowing it to slip away from traditional investigative actions [13]. The most common application of blockchain technology is Bitcoin, which is increasingly becoming a tool for criminal activities on the dark web [14]. With the help of blockchain solutions, you can track evidence during the entire duration of the investigation, from the scene of the crime to the court session, while ensuring transparency, integrity, and immutability. Blockchain can provide reliable informational support to investigative bodies of criminal justice, court bodies, and prosecutors in decision-making in criminal proceedings. The implementation of blockchain technologies in the practice of law enforcement agencies will make it possible to reduce the level of false convictions, ensure the honesty and transparency of the criminal justice system, and increase trust in it.

As international practice demonstrates, penitentiary institutions not only do not change prisoners for the better in most cases make them inveterate criminals. Significant parts of crimes are committed by people who have been convicted earlier. Recidivism research is limited as only some countries keep such statistics on the national level. This makes it difficult to research the problems in this area. However, even a small range of studies proves of existing a significant percentage of criminal recidivism: about 70% in the UK, 60% in France, and 55% in the USA [15]. The estimation of the number of convicted recidivists varies across countries significantly. The widespread implementation of the technology of storing data in a blockchain could ensure not only transparent and reliable storage of criminal records but also comparability and the possibility of exchanging information about criminals between different countries. However, criminal recidivism is a serious global issue and a threat to either the internal security of individual states or international security in general. This further confirms the need for research on recidivism at the national level. Identifying risk factors of criminal recidivism among convicts is an essential part of their adaptation to society after imprisonment and the prevention of recidivism.

The purpose of this research is to recognize the main individual characteristics of prisoners that have the greatest influence on the probable tendency for criminal recidivism.

2. Related Work

The importance and ambiguity of the problems of applying innovative methods and data science in the activities of law enforcement agencies increasingly prompt scientists from different countries of the world to study the effectiveness of various policing strategies [16–20]. M. P. Basilio, V. Pereira, and M. W. C. M. d. Oliveira studied and presented an overview of research conducted by various authors in the field of crime control in various countries over the past 50 years [21]. This greatly simplified data analysis in this area for other researchers and provided important information for our research. F. Dakalbab et al. conducted a systematic literature review on the application of AI tools in crime prediction [22]. A. Sangani et al. presented a brief overview of various research works devoted to the application of data mining methods in crime analysis [23]. Researchers pay considerable attention to the application of the predictive policing strategy in the work of law enforcement agencies [24–26]. M. A. Andresen and T. K. Hodgkinson applied negative binomial and binary logistic regressions to evaluate the impact of the police foot patrol [27]. M. A. Andresen and J. L. Shen evaluated the impact of foot patrols on crime [28].

A number of scientists tried to determine the factors that affect the quantity of crime recidivism at the state and interstate levels [29–31]. However, the existing discrepancy in the dataset sample, the definition of the concept of "recidivism", and the observation duration prevented them from obtaining reliable and highly-quality results. The majority of the research on this topic is devoted to the analysis of the influence of mental disorders or psychotropic substances on recidivism cases [32,33]. A. Karlsson and A. Håkansson studied the relationship between the use of specific psychoactive substances (ranked by a severity index) and recidivism. Risk factors for criminal recidivism were assessed using Cox regression analysis [34]. L. A. Jacobs et al. created a linear regression model to identify general risk factors for recidivism among two groups of individuals with serious mental disorders: with co-occurring substance use disorders or without them [35]. The comparative analysis results of recidivism rates in different countries confirmed that international data are not comparable [15,36]. The development and implementation of artificial intelligence solutions and blockchain technology open up new opportunities for using big data to prevent and predict criminal offenses [37,38]. P. Chen, J. Kurland, and S. C. Shi used a binary logistic regression approach to check the effectiveness of using AI and machine learning methods in predicting future crime in a case study of Beijing thieves and burglars [39]. D. Anderes et. al studied the possibility of the effective use of blockchain technology to store evidence in criminal cases and provide an efficient solution. Researchers have found that storing evidence on a blockchain can reduce the problems of loss, forgery, and manipulation of evidence [40]. Interpol is implementing a special project to prevent the use of blockchain technology by criminals. The project is financed by the European Union and is worth EUR 5 million. It is aimed at developing technical solutions to investigate and combat crimes and terrorism primarily related to virtual currencies and underground market operations. The goal of the project is to ensure legality while respecting users' legitimate right to privacy [41].

In Ukraine, the application of data science and innovative strategies in the activities of criminal justice bodies is only at the initial stage [11,35,36,42]. Therefore, national research is relevant to identify factors that influence the commission of repeated criminal crimes.

3. Background

There has been a rapid and unrelenting increase in the number of prisoners in recent decades in most countries of the world. Nowadays, there are more than 10 million of them according to World Prison Brief [43]. The reasons for the increasing number of prisoners are complex and ambiguous in different countries. However, their consequences are obvious. Prison overpopulation leads to the overcrowding of penitentiaries. As result, it causes inhumane, degrading conditions of detention, reduces the ability of penitentiary systems to control all groups of prisoners, increases the risk of conflict in a prison, and poses a serious threat to public safety. Furthermore, the maintenance of prisoners is expensive and carries a significant burden on the state budget. Therefore, a range of countries has made a clear political decision to reduce the prison population. Most European states have already introduced the institution of probation [44]. Alternative measures to imprisonment are used for those convicted of minor crimes in these countries. It guarantees a significant saving of state funds, and the accused acquires a real chance to socialize and provide for themselves and their families. Ukraine ranks 41st in the prison population rating among 223 countries of the world.

In Ukraine, the total prison population (including pre-trial detainees and prisoners) as of December 2022 is 48,038 (not including prisoners in Crimea, Sevastopol, Donetsk, and Luhansk regions that are not under the control of the Ukrainian authorities) [43]. It only adopts international experience in the area of prevention of criminal offenses by probation authorities. However, the issue of public safety remains decisive. In today's digital society, criminals are increasingly using AI and blockchain technologies to commit crimes [45]. The same technologies should be used by law enforcement agencies to prevent and solve criminal crimes. Artificial intelligence applications, blockchain technologies, and big data have opened a new era of unique opportunities for fast and high-quality collection, analysis and data, and interpretation of connections and patterns in criminal records. These tools are designed to help criminal justice agencies not only detect but also predict and prevent crime. Law enforcement agencies need to clearly realize who among the convicts is most likely to threaten society and may commit a repeat crime in the future. Nowadays, clear effective solutions are required based on the qualitative results of various scientific research on this issue. The purpose of this work is to determine the factors that have a significant impact on the tendency of convicts to recidivism. Such information will provide reliable support to the justice authorities in decision-making regarding freedom restriction, crime prevention, and the prevention of repeated criminal offenses (recidivism) in the future.

4. Materials and Methods

This study reviewed data from nearly 13,000 Ukrainian felons, who are detained in Ukrainian penitentiary institutions, to ascertain the significant factors (statistical and individual characteristics) that determine the propensity of offenders to commit repeated criminal offenses.

The following attributes were used in the applied research:

- Recidivism (binominal): 1—yes; 2—no;
- Sex (binominal): 1—male, 2—female;
- Age (nominal): 1—to 18 years old, 2—18 to 30 years old, 3—30 to 45 years old; 4—over 45 years old;
- Age1: (age at the time of the first conviction (to the actual degree of punishment), integer): 1—to 18 years old, 2—18 to 30 years old, 3—30 to 45 years old; 4—over 45 years old;
- Age2: (age at the time of the first conviction (suspended or actual sentence), integer): 1—to 18 years old, 2—18 to 30 years old, 3—30 to 45 years old; 4—over 45 years old;
- Marital status (binominal): 1—single, 2—married;
- Education (nominal): 0—incomplete secondary, 1—secondary, 2—special secondary, 3—incomplete higher, 4—higher;
- Place of residence (place of residence to the actual degree of punishment, nominal): 1—rural area, 2—urban area;
- Type of employment (type of employment at the time of conviction (up to actual punishment), nominal): 0—unemployed, 1—part-time, 2—full-time;
- Early dismissals (availability of early dismissals, binominal): 0—no, 1—yes;
- Motivation for dismissal (binominal): 0—no,1—yes;
- Real convictions (number);
- Suspended convictions (number).

Using the RapidMiner Studio tool for mining, we built the following machine-learning models [46–48] for predicting the tendency of convicts to commit criminal recidivism:

- Generalized Linear Model: generalization of linear regression models;
- Deep Learning: multi-level neural network for learning non-linear relationships;
- Decision Tree: finds simple tree-like models which are easy to clarify;

- Random Forest: an ensemble of multiple randomized trees;
- Gradient Boosted Trees: powerful but complex model using ensembles of Decision Trees;
- Support Vector Machine: powerful but relatively fast model, especially for non-linear relationships.

The GLM generalized linear regression models are an extension of classical linear models that can be used to model relationships between dependent attributes and one or more independent attributes. This method uses the maximization of the log-likelihood for adapting GLM to the dataset. The parameter's model regularization is conducted by elastic net penalty.

Deep Learning is a method of machine learning. It uses a multi-layer feed-forward artificial neural network. The neural network is trained with stochastic gradient descent using back-propagation. The number of hidden layers is unlimited. These layers are composed of neurons with rectifier function, tanh function, and max-out activation function. Advanced features (rate annealing, adaptive learning rate, dropout, L1 or L2 regularization, and stimulus training) allow for high predictive accuracy. Each calculated node asynchronously trains a copy of the overall model parameters on its branch data with multi-threading and transitively to the overall model by model-averaging along the network.

Algorithms of decision tree construction are based on the application of methods of regressive and cross-correlation analysis. One of the most popular algorithms of this family, CART (Classification and Regression Trees), is based on the separation of data in the branch of a tree on two daughter branches. Thus, the further division of that or the other branch depends on how much data are described by this branch. The division is conducted on the basis of the highest described branch of data coefficient of correlation between parameters according to that division, and the parameter must be envisaged in the future.

A random forest is a class of some number of random trees, with a certain number of trees declared as the parameter. These techniques can be used to predict either continuous attributes (regression problems) or categorical attributes (classification problems). The randomized trees are built (trained) on bootstrapped sub-sets of the input dataset. Each node of a randomized tree depicts a separating rule for one certain attribute. A sub-set of dataset attributes defined with the subset ratio criterion is regarded for the separating rule selection. The rule selection splits values in the most appropriate sequence of actions for the selected certain parameter criterion. For classification, the rule splits value appointments into several class predictions (nodes). The split is conducted while regression splits them to reduce the estimation error. Separating to new class prediction is repeated until the limited criteria value is given.

A gradient-boosted model is a powerful algorithm that can be used for regression or classification tasks. They are forward-learning methods classes. Regression and classification-boosted models obtain a predictive attribute value by incrementally improved evaluations. Boosting is a flexible nonlinear regression algorithm that gives an opportunity to enhance the accuracy of gradient-boosted trees. By serially using feeble classification procedures to the bit-by-bit changed dataset, assembles of decision trees are built that algorithmize a class of feeble forecasting models.

The Support Vector Machine (SVM) is a data analysis method for classification and regression analysis using models with supervised learning. SVM applies training algorithms for a given set of training examples, each of which is known to belong to one of two given categories. The SVM model assigns new samples to one of these two categories based on a non-probabilistic binary linear classifier. The SVM model depicts new examples as points in an n-dimensional space. In this representation, examples assigned to different categories should be separated by a clear boundary and be as far away from each other as possible.

The simplest assessment of model efficiency is total accuracy. This measure determines how accurate the positive predictions are, that is, what percentage of convicts identified as prone to recidivism virtually are recidivists. It is calculated as a percentage of correctly classified samples:

$$Accuracy = \frac{Number\ of\ correct\ prediction}{Total\ number\ of\ prediction}. \tag{1}$$

There is another way to calculate accuracy for binary classification by the following formula:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}, \tag{2}$$

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

Precision is a fraction of correctly identified positive cases:

$$Precision = \frac{TP}{TP + FP}. \tag{3}$$

Precision measures the fraction of actual positives that were identified correctly, and recall measures the coverage of actual positive cases.

The model is acceptable if its precision and recall are high:

$$Recall = \frac{TP}{TP + FN}. \tag{4}$$

Specificity is a score estimation of detection of the actual negative samples (what percentage of convicts who are not recidivists are predicted to be prone to recidivism):

$$Specifity = \frac{TN}{TN + FP}. \tag{5}$$

Since the mislabeling of a non-recidivist convict as prone to criminal recidivism has the greatest impact, in our case, the specificity model should be sufficiently high.

F-measure is computed as the harmonic mean of precision and recall. Each of these measures is given the same weighting.

The receiver operating characteristic curve (ROC curve) is a plot representing the quality estimates of binary classification. It visualizes the relationship between the number of true positives objects and the total number of false positives objects (also known as the error curve). The higher the AUC (the plot is located as close as possible to the upper left corner of the chart), the higher quality of the model.

5. Results

Among the built models, the highest accuracy (98.3%) is demonstrated by Decision Tree, Random Forest, and Gradient Boosted Trees (Figure 1).

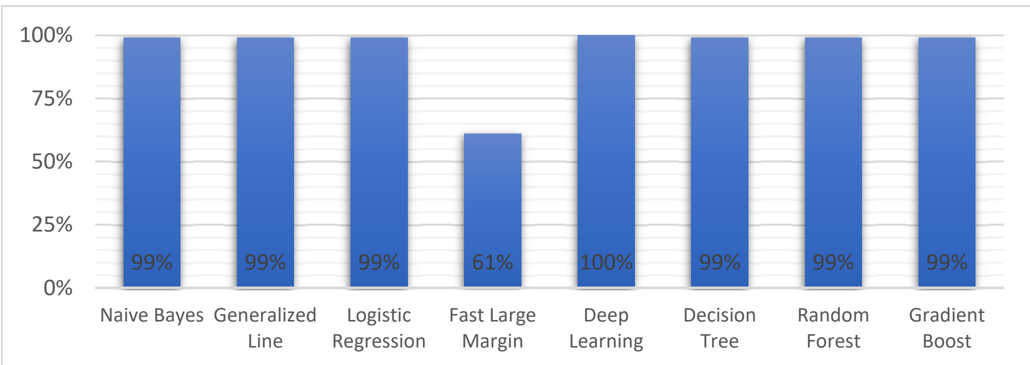

Figure 1. The accuracy chart for the machine learning models.

The following models: Fast Large Margin (98.7%), Decision Tree, Random Forest, and Gradient Boosted Trees (97.7%) present the highest precision (Figure 2).

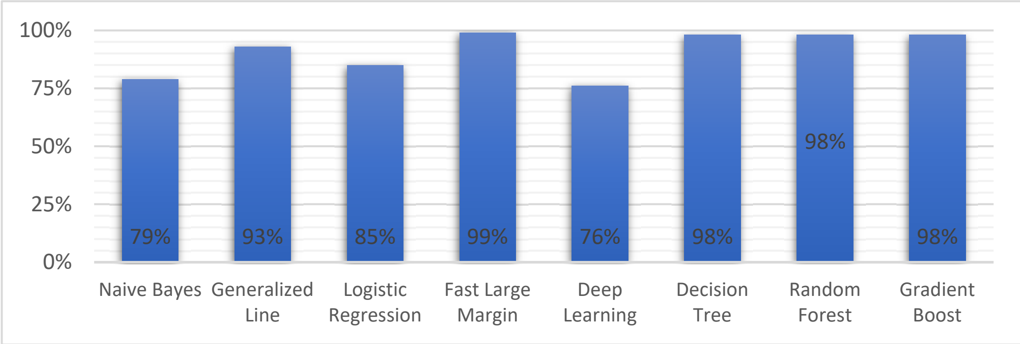

Figure 2. The precision chart for the machine learning models.

The highest recall is observed in Naive Bayes, Logistic Regression, and Deep Learning models (99.5%) (Figure 3).

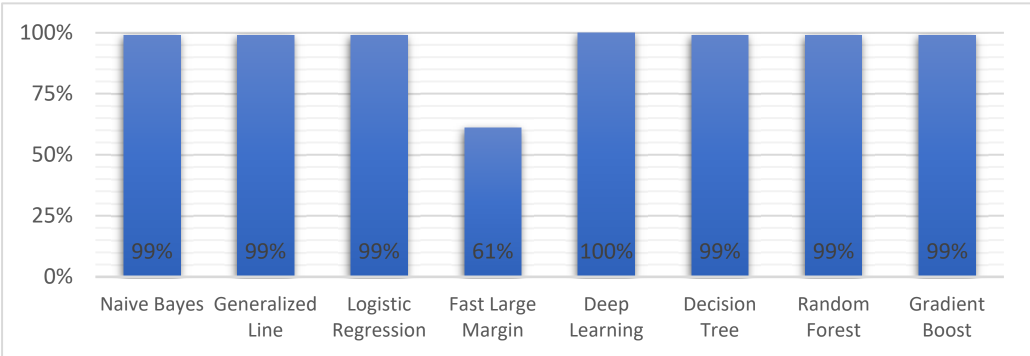

Figure 3. The recall chart for the machine learning models.

Decision Tree, Random Forest, and Gradient Boosted Trees models have the highest sensitivity (98.8%), which is shown in Figure 4.

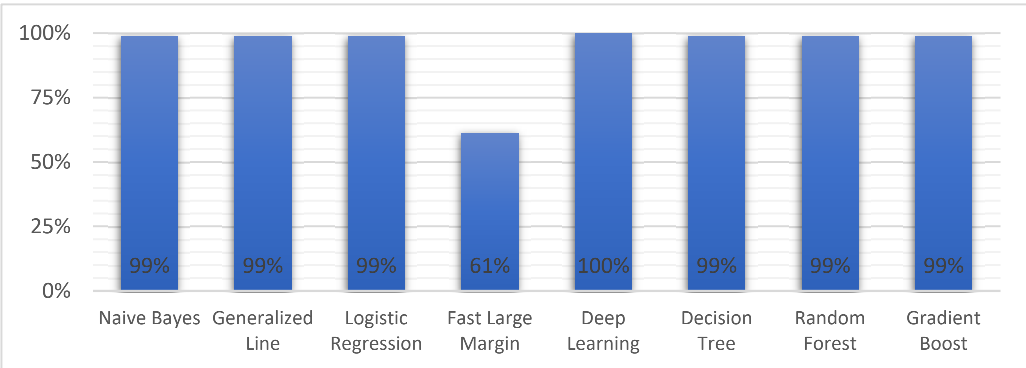

Figure 4. The sensitivity chart for the machine learning models.

Fast Large Margin (99.2%), Decision Tree, Random Forest, and Gradient Boosted Trees (97.8%) have the highest specificity (Figure 5).

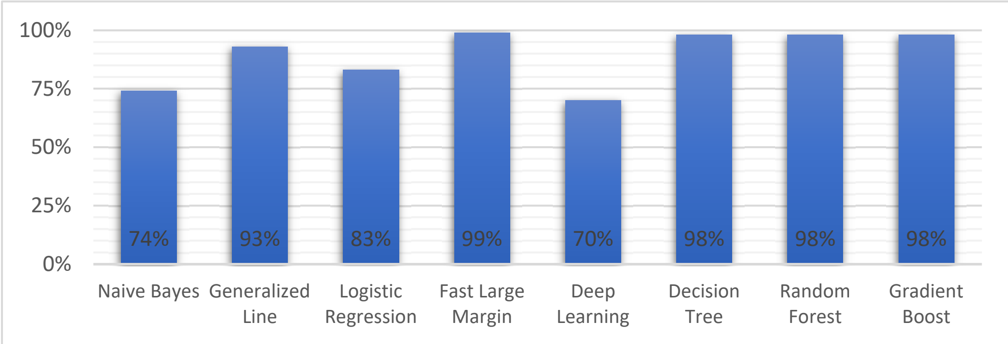

Figure 5. The specificity chart for the machine learning models.

In general, The Decision Tree model classifies prisoners as prone or not prone to criminal recidivism in the best way according to the obtained quality and accuracy estimation of the constructed models (Table 1). This is confirmed by the Roc Surveys (Figure 6).

Table 1. Comparison evaluation tables for machine learning models.

Model	Accuracy	Precision	Recall	F Measure	Sensitivity	Specificity	AUC
Naive Bayes	86.7%	78.9%	99.5%	88.0%	99.5%	74.4%	0.96
Generalized Linear Model	95.8%	92.8%	99.1%	95.8%	99.1%	92.6%	0.99
Logistic Regression	91.1%	85.0%	99.5%	91.7%	99.5%	83.1%	0.99
Fast Large Margin	80.5%	98.7%	61.3%	75.6%	61.3%	99.2%	0.99
Deep Learning	84.4%	76.1%	99.5%	86.3%	99.5%	69.6%	0.99
Decision Tree	98.3%	97.7%	98.8%	98.3%	98.8%	97.8%	0.99
Random Forest	98.3%	97.7%	98.8%	98.3%	98.8%	97.8%	0.99
Gradient Boosted Trees	98.3%	97.7%	98.8%	98.3%	98.8%	97.8%	0.99

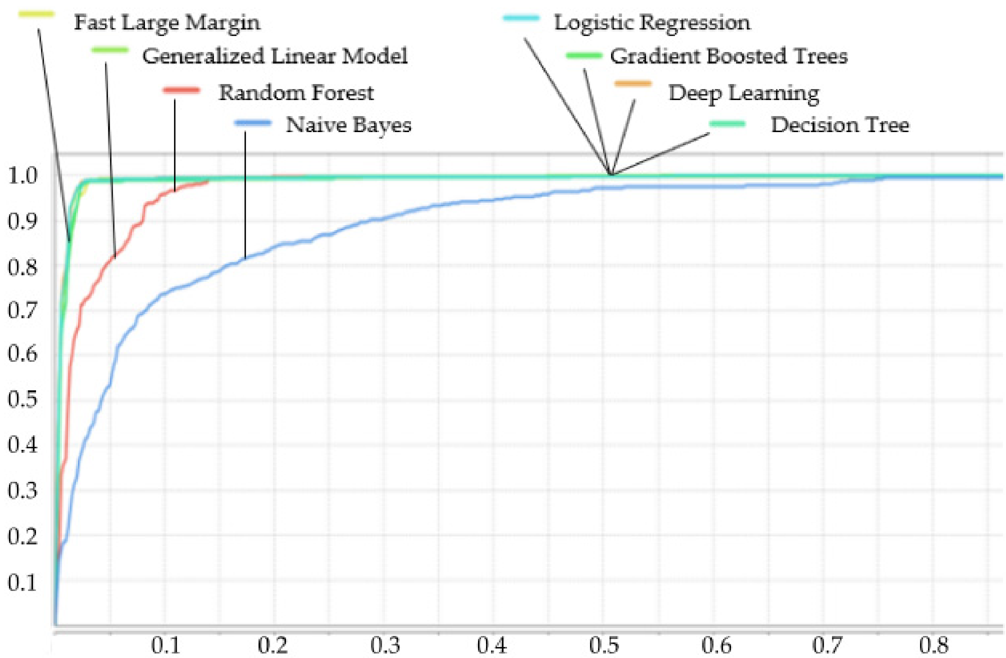

Figure 6. The ROC curves for the machine learning models.

The quantitative interpretation of ROC is the AUC indicator (Area Under Curve). This is an estimation area bounded by the ROC curve and the axis representing the number of false positives. A classifier is better if the AUC is higher. The model is unsuitable if the AUC indicator is not greater than 0.5.

Each of the used machine learning models has a very high AUC (at least 0.96) (Figure 7).

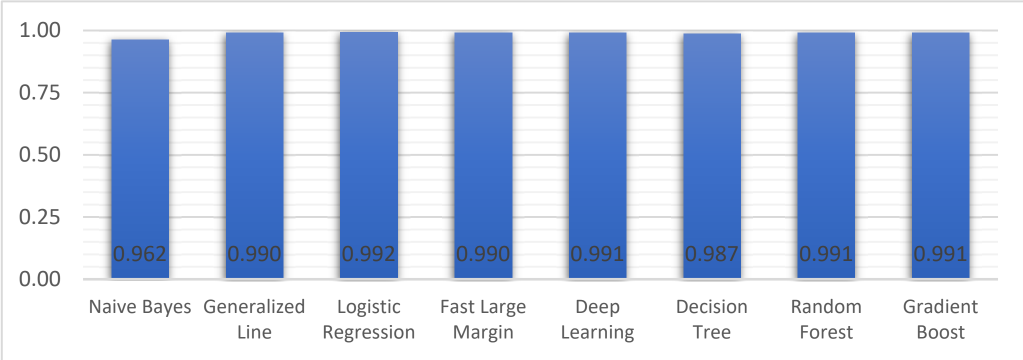

Figure 7. The AUC chart for the machine learning models.

Decision Tree, Random Forest, and Gradient Boosted Trees models provide the highest quality and precision scores among all other created models. Decision Trees are most often applied to solving classification problems when the target attributes are binomial, as in our case. Table 2 presents the high estimation of the sensitivity and specificity of created models. This is paramount for our investigation when one's freedom depends on decision-making.

Table 2. Confusion matrix for Decision Tree models.

Title 1	True 2	True 1	Class Precision
pred 2	1844	21	98.88%
pred 1	42	1808	97.73%
class recall	97.77%	98.85%	

We conclude that the attributes Real convictions (0.680), Convictions (0.625), Early dismissals (0.493), Age2 (0.394), and Age1 (0.89) make the greatest contribution to the distribution of convicts prone or not prone to criminal recidivism, according to the weights chart (Figure 8) which is an influence graphical representation of the attributes on the predictive results.

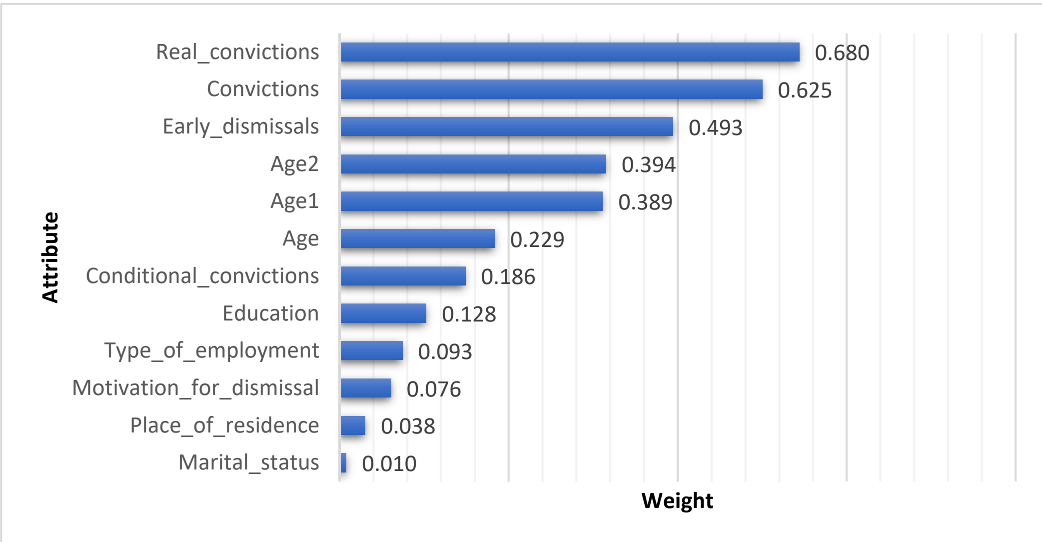

Figure 8. Weights by Correlation.

So, the younger and more often a person attends court and prison, the more likely this person is to return. A significant factor is also the feeling of impunity, which provokes new crimes.

A Lift Chart is a graphical representation of model performance. It is built by calculating the ratio between the result obtained using the model against the result obtained without one.

For any given number of cases (values on the X-axis), the expected number of positive results is presented when predicting without a model but only based on randomly selected cases. This is the standard by which the performance of the model is evaluated. The bar chart provides the number of true positive cases in each group (in 10 deciles).

The constructed decision tree chart visualizes the algorithm for the distribution of prisoners into groups prone or not prone to commit future criminal offenses (Figure 9).

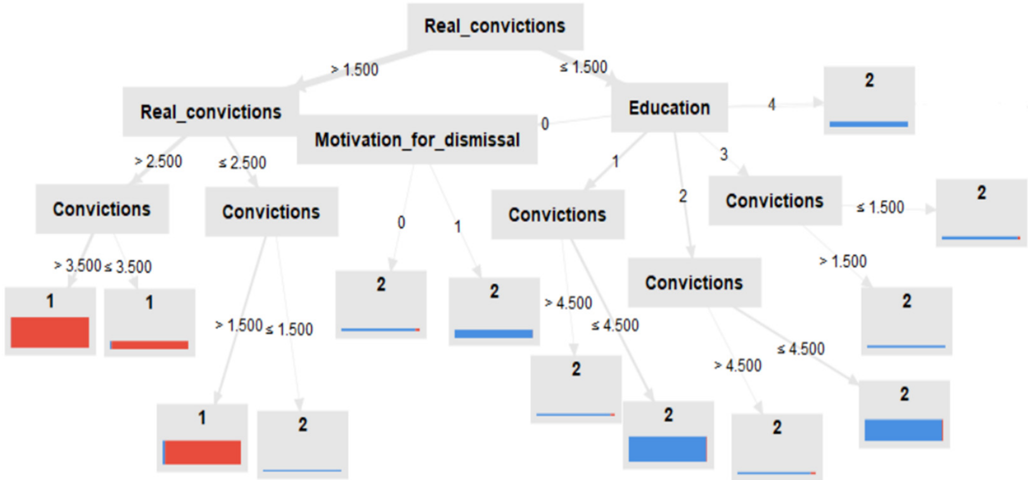

Figure 9. Decision Trees model plot.

The Lift Chart explains the obvious advantage of using the Decision Trees model for predicting the probability of recidivism by convicts (Figure 10).

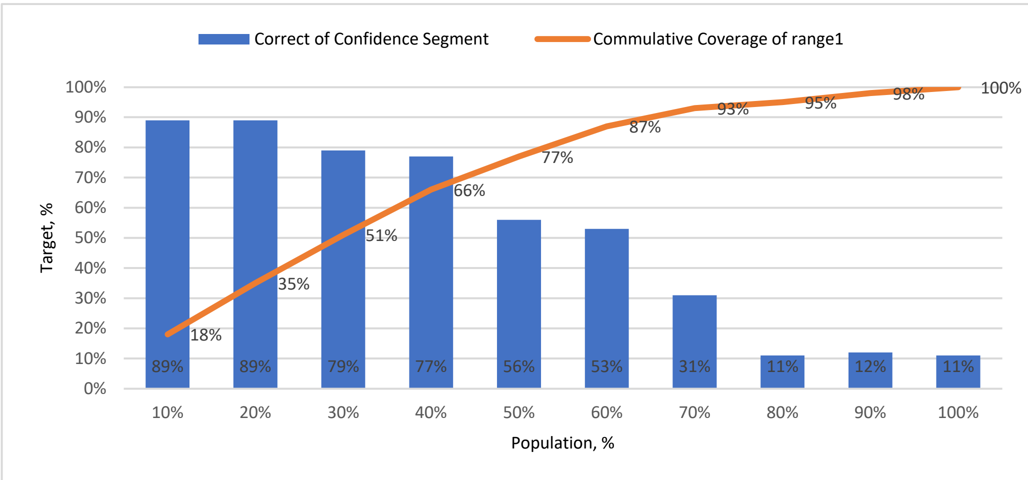

Figure 10. Lift Chart for the Decision Trees model.

The created model confirms the falsity of the thesis that all convicts are recidivists, and it predicted a 67% probability of convicts' propensity for criminal recidivism (Figure 11).

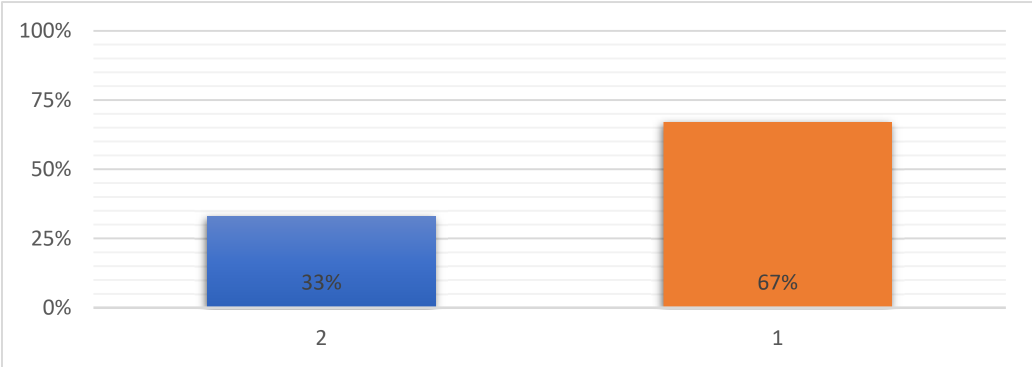

Figure 11. Lift Chart for the Decision Trees model.

The number of convictions with real punishment (Real convictions), the number of convictions with suspended or real punishment (Convictions), and the type of employment (Type of employment) became the most significant when assigning convicts to the group prone to criminal recidivism in the future (Figure 12).

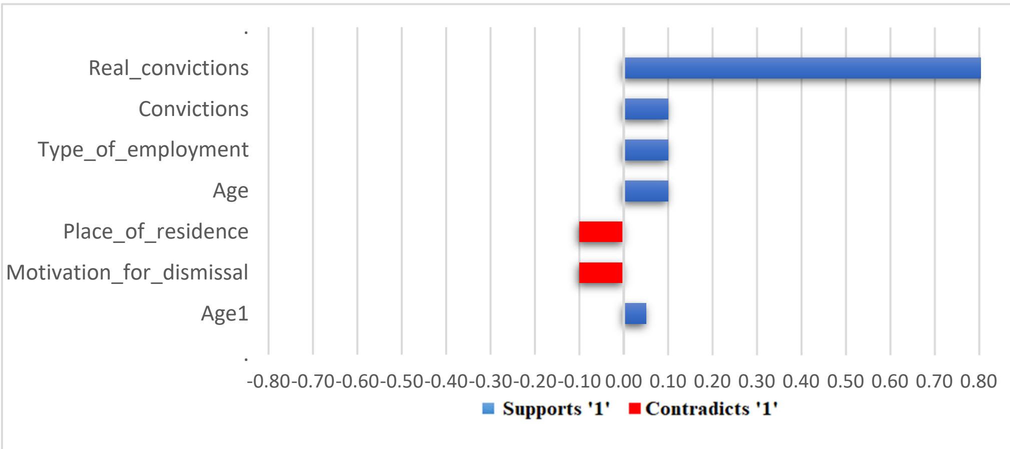

Figure 12. Important factors for "Recidivism" = yes.

The highest correlation of data attributes was found between the age of the first conviction to a suspended or real sentence (Age1) and the number of convictions to a suspended or real sentence (Real convictions), the number of imprisonments (Convictions), and the presence of suspended convictions (Suspended convictions) (Table 3). The earlier the inmate committed his first criminal offence (Age1 = 1, Age1 = 2), the more likely he was to be rehabilitated by the justice system, and the more likely he committed criminal recidivism. For the category of inmates who were sentenced after adulthood (Age1 = 3), there is an inverse correlation between the attributes: the majority of them did not have suspended convictions or early releases, and they are less likely to be prone to commit repeated criminal offences.

Table 3. Correlation matrix (fragment).

Attributes	Age1 = 1	Age1 = 2	Age1 = 3	Early_dismissals = 1	Convictions	Real_convictions
Early_dissmissals = 1	0.133	0.093	−0.154	1	0.421	0.42
Convictions	0.254	0.099	−0.225	0.421	1	0.834
Real_convictions	0.291	0.075	−0.236	0.412	0.834	1
Conditional_convictions	0.055	0.074	−0.079	0.188	0.648	0.121

For each of the convicts from the dataset, the probability of criminal recidivism in the future was determined, and significant factors affecting his propensity to repeat crimes were determined (Table 4).

Table 4. Decision Tree prediction (fragment).

Row No.	Recidivism	Prediction (Recidivism)	Age 1	Age 2	Number of Convictions	Early Dismission
2970	1	0.904	1	1	2	1
2971	1	0.904	2	1	9	1
2972	1	0.904	1	1	2	1
2973	1	0.904	1	1	0	1
2974	1	0.389	2	2	0	0
2975	1	0.904	2	1	3	1

The model simulation for a prisoner aged 30 to 45 years old (Age = 3) who was convicted for the first time at the age of 18 to 30 years old (Age1 = 2) and had an early dismissal (Early dismissals = 1) demonstrated an 83% forecast of the probability of criminal recidivism (Figure 13).

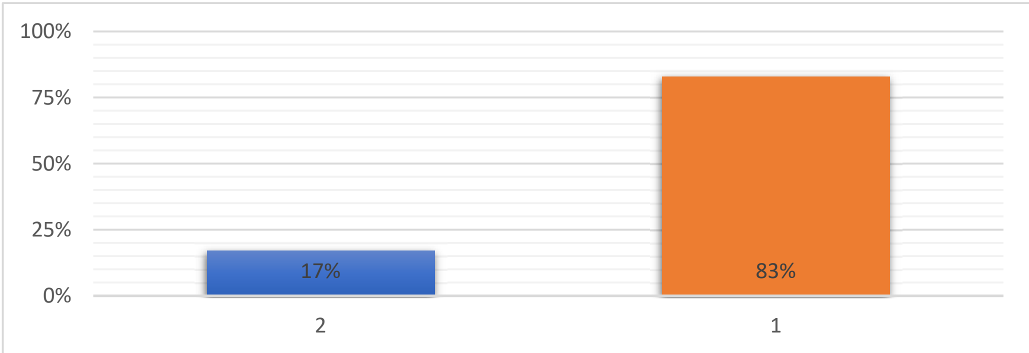

Figure 13. Most likely for "Recidivism" = yes.

6. Discussion

When separated into groups, the essential factor is the number of real convictions. For criminals who are serving their first or second sentence, the level of education is a significant factor. The more educated the felon, the less likely he/she is to commit criminal recidivism. An interesting fact is that for convicts who have not completed secondary education (Education = 0), a significant factor is the existence of motivation for release. Convicts who are motivated to be released are less prone to criminal recidivism. For prisoners who are serving at least the third sentence, the number of convictions to suspended or real punishment is a vital factor in the tendency to recidivism. This fact highlights that suspended convictions create the illusion of impunity and "provoke" repeated crimes.

The Generalized Linear Model, Deep Learning, Decision Tree, Random Forest, Gradient Boosted Trees, and Support Vector Machine were applied for predicting the probability of propensity for criminal recidivism of felons of Ukrainian penitentiary institutions. The obtained models were compared. It was established that the use of the Decision Trees model for predicting the probability of recidivism by convicts has obvious advantages.

The Decision Tree model was developed to determine the highly significant factors of felons' propensity to recidivism. It predicted a 67% probability of convicts being prone to criminal recidivism. It was found that the number of previous convictions to the real punishment, the number of convictions to the suspended or real punishment (which includes the existence of suspended convictions), and the type of employment have the greatest weight for classifying convicts as prone or not prone to recidivism. The earlier the prisoner committed his first crime, the more loyal the judicial system was to him. This created the illusion of impunity and provoked the commission of repeated criminal offenses.

Prisoners who were convicted after coming of age were not given additional chances of correction by the justice system. Most had no probation or parole and were less likely to re-offend.

For each of the 13,000 convicts from the dataset, individual influencing factors were determined. For example, a model simulation for a prisoner aged 30 to 45 years old, who was convicted for the first time at the age of 18 to 30 years old and had early releases, with 83% probability predicted committing criminal recidivism in the future. This information will be useful for law enforcement agencies when making a decision on parole or taking preventive measures against recidivism after the release of convicts.

The model can be applied to new cases. The created Decision Tree model provides useful information for justice authorities regarding the possibility of applying a suspended punishment, parole, or participation in probation to a particular convicted person. The obtained results can provide informational support for conducting an effective criminal justice policy in Ukraine, in particular, during optimal decision-making regarding the use of an appropriate system of prevention, punishment, or implementing the institution of probation.

The next stage of our research will be the analysis of the possibility of using the technology of distributed registers/blockchains in predictive criminology. The share of crimes moving from physical space to cyberspace is growing exponentially. Nowadays, more than ever, we need adequate technologies to protect against crimes, in particular, cybercriminals. The use of blockchain technology can become an effective tool that will ensure the reduction of the impact of crime on victims and society and become the basis for the creation of new predictive criminology.

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