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Support vector machine to criminal recidivism prediction

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***Abstract*—Internal security of the state is one of the prerequisites for sustainable development. To ensure the public safety and personal security of citizens, it is necessary to develop effective measures to reduce crime and prevent crime in the future. The starting point for the development and practical implementation of an effective strategy to combat crime or prevent certain crimes is criminological forecasting. Individual forecasting is aimed at determining the possibility of committing a crime (crimes) in the future by a certain person or group of persons.**

For risk assessment, the following are traditionally used machine learning models. Such models also provide qualitative assessments in the scientific prediction of the likelihood and possibilities of committing a repeat criminal offense. Knowledge gained from the application of machine learning algorithm, can provide justice authorities with anticipatory information that is essential for developing a general concept of combating crime. The development of applied models for crime analysis and forecasting can become a reliable tool to support decision-making in predicting likely criminal behavior in the future and ensuring the internal security of the state. In this paper, the results of the application are presented by the machine-learning algorithms Support Vector Machine (SVM) for assessment of the risk of recidivism of criminal offenses by persons who have already been convicted of such a crime in the past. The data set consisted of the 12,000 criminal defendants' criminal profile information in Ukraine. The constructed classifier has a high precision (98.67%), recall (97.53%) and is qualitative (AUC is equal 0.981). The created SVM model can be applied to new data set to predict the risk of reoffending by convicted individuals in the future.

***Keywords*—machine learning algorithm; support vector machine; risk assessment; classification; criminal recidivism prediction**

I. Introduction

According to the "World Prison Population List" more than 10.77 million convicts are serving their sentences in penitentiary institutions in the world (latest available at 1.10.2021). Considering the data about the missing prisoners, that are not taken into account in official prison population totals, the full total may well be in excess of 11.5 million [1]. The world prison population's total continues to grow at almost the same rate as, the world's general population (24% compared to the world prison population's total compared to 28% for the world's general population since 2000). The largest number of prisoners at the end of 2021 was observed in the United States. Only in Europe the total prison population has decreased since 2000. In Ukraine, at the end of 2021, 49,211 prisoners were serving a sentence in the form of the penalty of imprisonment. It had an average level of danger. In 2022 the Global Risk Assessment recognized Ukraine as one of the most dangerous countries in the world due to the full-scale war unleashed by Russia on the territory of Ukraine [2]. According to World Population Review analysts, Ukraine is ranked 57th out of 136 in the ranking of countries with the highest crime rate at the beginning of 2023. Its rate was 47.42 crimes per 100,000 inhabitants, while the United States took the previous place with 47.81 crimes per 100,000 inhabitants. In 2023, the largest number of crimes was committed in countries with high poverty and unemployment rates, including Venezuela, Papua New Guinea, and South Africa. The lowest crime rates in the world are recorded in countries where law enforcement agencies work very effectively. These are Denmark, Norway, Switzerland, Japan, and New Zealand. Strict police control and strict legislation help to reduce the crime rate in the country [3].

The efficiency of law enforcement agencies directly depends on the effectiveness of the tools they use in their information and analytical activities. Practice shows that the risk of recidivism is much higher than the risk of the initial crime [4, 5]. A person who has already been convicted of a criminal offense in the past is much more susceptible to the effects of acculturation (adopting elements of the criminal subculture) and stigmatization (branding of differences from others based on criminal record, involvement in criminal traditions). These factors should be taken into account when predicting the likelihood of committing a particular crime.

One of these tools is predictive policing. Its means applying mathematics and analytical methods to the detection of possible relationships and non-obvious patterns in criminal records. One of the priority areas of predictive policing is predicting the risks of criminal offenses, including criminal recidivism, which pose a high risk to citizens and society. An effective internal security system is an essential condition for the external security of the country. Therefore, the problem of finding the optimal method for assessing the risks of criminal recidivism in the future, which will ensure accurate and reliable results that take into account the specifics of each particular dataset, remains relevant.

The purpose of this study is to assess the risks of future criminal recidivism by previously convicted offenders.

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II. Related work

Many scientists around the world are searching for effective tools that would provide effective support to law enforcement agencies in solving and preventing crimes [6, 7]. Machine learning algorithms for predicting the risks of criminal offenses in the future have proven to be particularly effective in practice [8, 9, 10, 11]. M. Azizi used machine learning models to remand risk assessment and reduce the pretrial population [12]. S. W. Palocsay et al. used neural network models to classify the population into two categories: non-recidivists and eventual recidivists [13]. C. Wang et al. studied interpretable recidivism prediction using machine learning models and analyzing performance in terms of prediction ability, sparsity, and fairness [14]. S. Etzler et al. compared the predictive performance of the random forest compared with logistic regression on a sample of adult male individuals convicted of sexual offenses [15]. S. Walczak researched the application of neural networks for forecasting crime and other police decision-making [16]. D. Watts et al. developed a machine learning model to predict the type of criminal offense committed in a large transdiagnostic sample of psychiatry patients, at an individual level [17]. R. de la Cruz et al. analyze and explore criminal recidivism with different modelling strategies: based on an explanation of the phenomenon and based on a prediction task [18]. C. Na et al. analyzed the capabilities of the machine learning methods as alternative risk assessment tools for efficient decision-making and their competitiveness and utility in predicting future arrest outcomes [19]. F. Adesola et al. used Support Vector Machine based spatial clustering technique for violent crime prediction [20]. However, the problem of choosing the best method for predicting criminal recidivism and developing high-quality machine-learning models that provide reliable qualitative results remains relevant today.

III. Materials and Methods

This paper is a continuation of a series of studies on building an optimal criminal recidivism prediction model that takes into account the specific features of the dataset and provides reliable qualitative results. The previous papers consider the binary logistic regression model to predict the probability of criminal recidivism on the basis of individual statistical and dynamic characteristics of convicts [21]. We also built Decision Trees models for classifying convicts into two groups: those prone and those not prone to commit criminal recidivism in the future based on the analysis of their criminal records [7]. An intelligent scoring model was developed to identify the most significant factors that determine the probable propensity of prisoners to commit criminal recidivism [8]. In this paper, we propose to use the Support Vector Machine algorithm to assess the risk of criminal offenses by individuals, that are serving time pretrial detention.

The input example set is a table containing the following attributes (individual characteristics and information about previous criminal offenses) 12,000 prisoners, that were held in the prison system in Ukraine (Table I).

We used RapidMiner Studio tools [22] to build the Support Vector Machine algorithm We use these algorithms to predict the risk of recidivism by people who have already been convicted of criminal offenses.

TABLE I
THE CRIME RECORDS DATA

Attribute	Recidivism	Value
Recidivism	Recidivism	1 – yes, 0 – no
AFA	Age at the time of the first conviction to the actual degree of punishment	integer
AFC	Age at the time of the first conviction to the suspended or actual sentence	integer
Real Convictions	Number of real convictions	integer
Suspended Convictions	Number of suspended convictions	integer
Early Dismissals	Number of early dismissals	integer

A Support Vector Machine (SVM) is a linear machine-learning algorithm, that using for solving regression and classification problems. This algorithm has a wide range of applications and can be used to solve both linear and nonlinear practical problems. The SVM algorithm creates a line or hyperplane that divides data points into classes. The main task of the algorithm is to find the most appropriate line or hyperplane that divides data points into two classes. The SVM algorithm receives an example set as input and generates an "ideal" dividing line or hyperplane as output (named decision boundaries) [23].

The SVM algorithm searches for data points that are closest to the dividing line. These points are called support vectors. Next, the algorithm calculates the distance between the support vectors and the decision boundaries. This distance is called margin distance. The main goal of the algorithm is to maximize the margin distance. The best hyperplane is the one with the maximum margin distance. A hyperplane is an n-1 dimensional plane in an n-dimensional Euclidean space that divides the space into two separate parts.

Parameters are arguments that are passed when creating a classifier. The most important SVM parameters are C and Gamma. The C parameter is designed to adjust the fine line between the "smoothness" and the accuracy of the training sample classification. The higher the C value, the more objects in the training sample will be correctly classified. The Gamma parameter determines how far each of the elements in the data set influences the "ideal" decision boundary. The lower the Gamma value, the more elements are involved in the selection of decision boundaries. This applies even to elements that are located quite far from it. If the Gamma value is high, the algorithm will use only those elements that are closest to the decision boundaries. The points closest to each other have more weight in the decision.

The following loss function using to maximize the margin between the hyperplane and data points) [24]:

$$\left(x, y, f(x)\right) = f(x) = \begin{cases} 0, \text{ if } y \cdot f(x) \geq 1 \\ 1 - y \cdot f(x), \text{ else} \end{cases}, \quad (1)$$

or

$$c\left(x, y, f(x)\right) = (1 - y \cdot f(x))_{+} \quad (2)$$

The loss is equal to 0 if the empirical and the predicted values are of the same sign. In other cases will be computation the loss value. A regularization parameter balanced the margin maximization and loss.

The loss function is computed from the following equation:

$$\min_w \lambda\|w\|^2 + \sum_{i=1}^{n}(1 - y_i\langle y_i, w\rangle)_+. \quad (3)$$

Computed the partial derivatives with respect to the weights to find the gradients and updates the weights:

$$\frac{\delta}{\delta w_k}\lambda\|w\|^2 = 2\lambda w_k. \quad (4)$$

$$\frac{\delta}{\delta w_k}(1 - y_i\langle y_i, w\rangle)_+ = \begin{cases} 0, & \text{if } y_i\langle x_i, w\rangle \geq 1 \\ -y_i x_{ik}, & \text{else} \end{cases}. \quad (5)$$

If the SVM algorithm correctly predicts the classes of data points necessary to update the gradient from the regularization parameter:

$$w = w - \alpha \cdot (2\lambda w), \quad (6)$$

there is no misclassification.

If the SVM algorithm makes a mistake in the prediction of the categories of the data point, necessary take into account the loss along with the regularization parameter to a performs gradient update.

$$w = w + \alpha \cdot (y_i x_i - 2\lambda w), \quad (7)$$

there is a misclassification.

To assess the quality of models and compare different algorithms in machine learning problems, the following metrics are used (Table II).

TABLE II
METRICS

Attribute	Recidivism	Value
$\hat{y} = 1$	True Positive (TP)	False Positive (FP)
$\hat{y} = 0$	False Negative (FN)	True Negative (TN)

Here $\hat{y}$ is the answer of the algorithm for the object, y is the true label of the object. False Negative (FN) and False Positive (FP) are classification errors.

The percentage of correct answers is determined by the accuracy metric using the following formula:

$$accuracy = \frac{TP+TN}{TP+TN+FP+FN}. \quad (8)$$

To evaluate the quality of the algorithm on each of the classes separately, we use the precision and recall metrics:

$$precision = \frac{TP}{TP+FP}. \quad (9)$$

$$recall = \frac{TP}{TP+FN}. \quad (10)$$

Precision can be interpreted as the ratio of objects identified by the classifier as positive that are actually positive. Recall determines the ratio of objects from the positive class that the algorithm correctly identifies out of all the positive class objects.

Recall demonstrates the algorithm's ability to detect the data of a specific class overall, while precision determines the algorithm's ability to distinguish that class from other classes.

One way to evaluate the overall performance of a model is through AUC-ROC. It represents the area under the curve (AUC) of the receiver operating characteristic (ROC) curve. This curve is a line from (0,0) to (1,1) in the True Positive Rate (TPR) and False Positive Rate (FPR) coordinates:

$$TPR = \frac{TP}{TP+FN} \quad (11)$$

$$FPR = \frac{FP}{FP+TN} \quad (12)$$

Ideally, the ROC curve should strive (in the sense of approaching) the point (0,1).

To predict the risk of criminal recidivism by training a Support Vector Machine model on records of a person's criminal history of convicted, optimizing its core parameters C and gamma and scoring risk on new data we created the process, which consists of the 5 following steps:

1. Loading the example set containing attributes of individual characteristics and information about their past criminal offenses. For the criminals where a recidivism observation is missing, the recidivism risk should be predicted.
2. Editing, transforming, and loading (ETL) - splitting data into those rows that have a label value and those where the label value is missing. The rows with labels are used for training a model which should predict the recidivism risk for the rows without a label.
3. Training and optimizing the Support Vector Machine model to predict the risk of recidivism. The optimization operator altered the significant SVM parameters C and gamma to return a model with maximum prediction accuracy.
4. Using the optimized Support Vector Machine model, predict the likelihood of recidivism in the future.
5. Converting model optimization log to a data set.

The process operators are presented in Fig. 1-3 and Tables III-V.

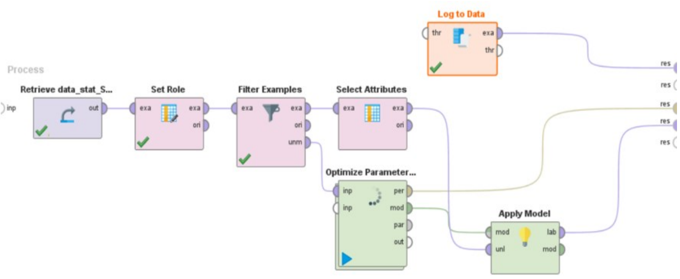

Fig. 1. Process operators of the SVM model to predict recidivism risk

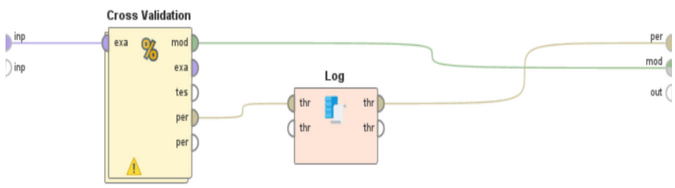

Fig. 2. Preprocessing operators of optimize parameters

TABLE III
SVM MODEL PROCESS OPERATES

Operator	Description
Load data	loads example set into the process
Set Role	changes the role of attributes
Filter Examples	selects which examples of an example set are kept or removed
Select Attributes	selects a subset of attributes of an example set and removes the other attributes
Optimize Parameters (Grid)	finds the optimal values of the selected parameters for the operators in its sub process
Apply Model	applies a model on an example set

TABLE IV
OPTIMIZE PARAMETERS PREPROCESSING OPERATES

Operator	Description
Cross Validation	executes the sub process for all combinations of selected values of the parameters and delivers the optimal parameter values through the parameter set a port
Log	performs a cross-validation to estimate the statistical performance of a learning model

The Cross Validation operator performs cross-validation, which consists of two sub processes (Fig. 3):

- Model Training – utilizes the Support Vector Machine model to train the dataset.
- Testing – applies the Apply Model operator to the test dataset and the Performance operator to determine the performance of applying the model to the test data.

Fig. 3. Preprocessing operators of Cross-Validation

TABLE V
OPTIMIZE PARAMETERS PREPROCESSING OPERATES

Operator	Description
Replace Missing Values	replaces missing values in examples of selected attributes by a specified replacement
SVM	support vector machine learner
Apply Model (2)	applies a model on an example set
Performance	performs a cross-validation to estimate the statistical performance of a learning model

IV. RESULTS AND ANALYSIS

The outputs of the classification model to predict the risk of criminal recidivism, based on the support vector machine: optimization log, performance of the best model, default predictions and confidence are presented in Tables VI-IX.

TABLE VI
LOG (FRAGMENT)

C	Gamma	Performance
radial	1.443	0.928
radial	0.035	0.889
radial	0.416	0.865
radial	1.443	0.979
radial	0.065	0.536
radial	0.065	0.851
radial	2.686	0.915
radial	0.010	0.840

TABLE VII
OPTIMIZE PARAMETERS (GRID) (FRAGMENT)

Iteration	SVM.kernel _gamma	SVM.C	Accuracy
5	0.129	0.001	0.859
9	1.443	0.001	0.876
18	0.414	0.010	0.962
6	0.224	0.001	0.863
19	0.775	0.010	0.934
10	2.686	0.001	0.862
3	0.035	0.001	0.837
52	0.775	10.000	0.979
20	1.443	0.010	0.928
36	0.035	1.000	0.889

TABLE VIII
EXAMPLE SET (APPLY MODEL) (FRAGMENT)

Row No.	Predic-tion (Recidi-vism)	Confi-dence (1)	Confi-dence (0)	AFA	AFC	Real Convi-ctions	Suspe-nded Convi-ctions	Early Dismissals
527	1	0.870	0.130	21	18	3	3	1
528	1	0.732	0.268	21	17	2	2	1
529	1	0.734	0.266	23	20	6	1	1
530	0	0.268	0.732	20	17	1	1	1
531	1	0.867	0.133	19	17	3	2	1
532	1	0.731	0.269	28	22	2	1	1
533	1	0.732	0.268	22	17	2	1	0

TABLE IX
METRICS EXAMPLE SET (LOG TO DATA) (FRAGMENT)

Row No.	Iteration	SVM.kernel_ gamma	SVM.C	Accuracy
11	6	0.224	0.001	0.859
12	19	0.775	0.010	0.934
13	10	2.686	0.001	0.862
14	3	0.035	0.001	0.837
15	52	0.775	10.000	0.979
16	20	1.443	0.010	0.928
17	36	0.035	1.000	0.889
18	11	5	0.001	0.559
19	7	0.416	0.001	0.865
20	53	1.443	10.000	0. 979

The accuracy estimates of the machine learning model are presented in Tables X and Figs. 4-5.

TABLE X
PERFORMANCE VECTOR: ACCURACY
ACCURACY: 98.06% +/- 0.26% (MICRO AVERAGE: 98.06%)
PRECISION: 98.67% +/- 0.30% (MICRO AVERAGE: 98.67%) (POSITIVE CLASS: 0)
RECALL: 97.53% +/- 0.41% (MICRO AVERAGE: 97.53%) (POSITIVE CLASS: 0)

	True 1	True 0	Class Precision
Pred. 1	5901	156	97.42 %
Pred. 0	83	6163	98.67 %
Class Recall	98.61 %	97.53 %	97.42 %

The share of correct answers by the classifier is over 98%. The proportion of cases identified by the classifier as positive and actually positive is 98.67%. The classifier identified close to 97.53% of the objects of the positive class out of all the objects of the positive class.

We obtained high precision and recall scores. The application of the machine learning model shows minor errors in the results (Fig. 4). The created model can be considered acceptable. The machine learning model has a very high AUC: 0.981 +/- 0.004 (micro average: 0.981). The built classifier is of high quality (Fig. 5).

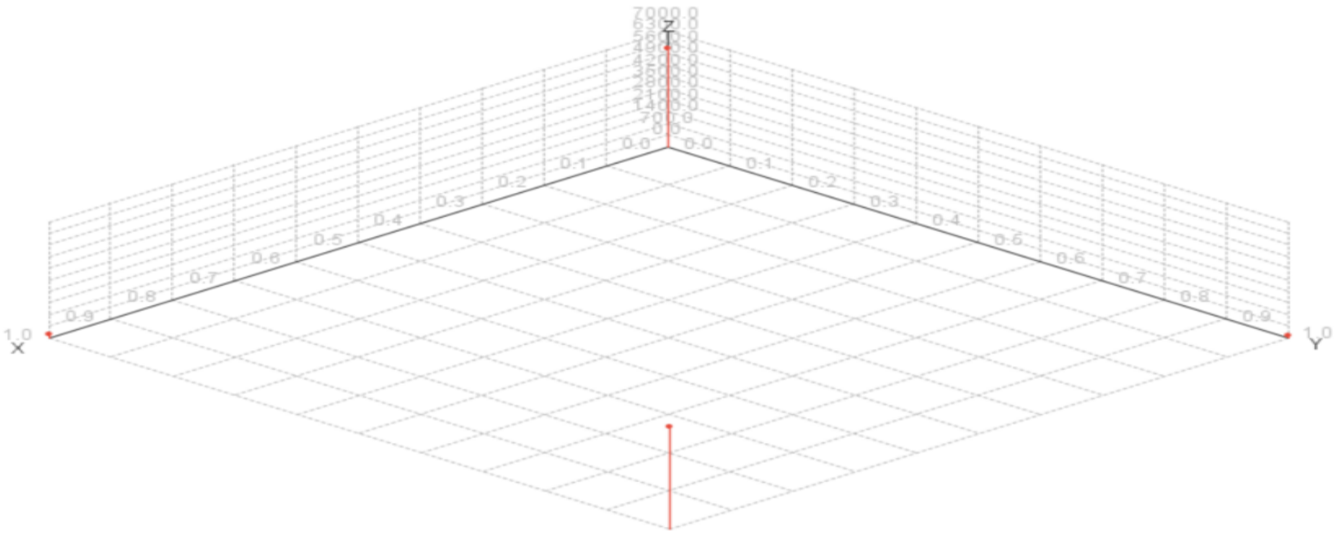

Fig. 4. The plot of the Confusion Matrix: Accuracy (x: true class, y: pred. class, z: counters)

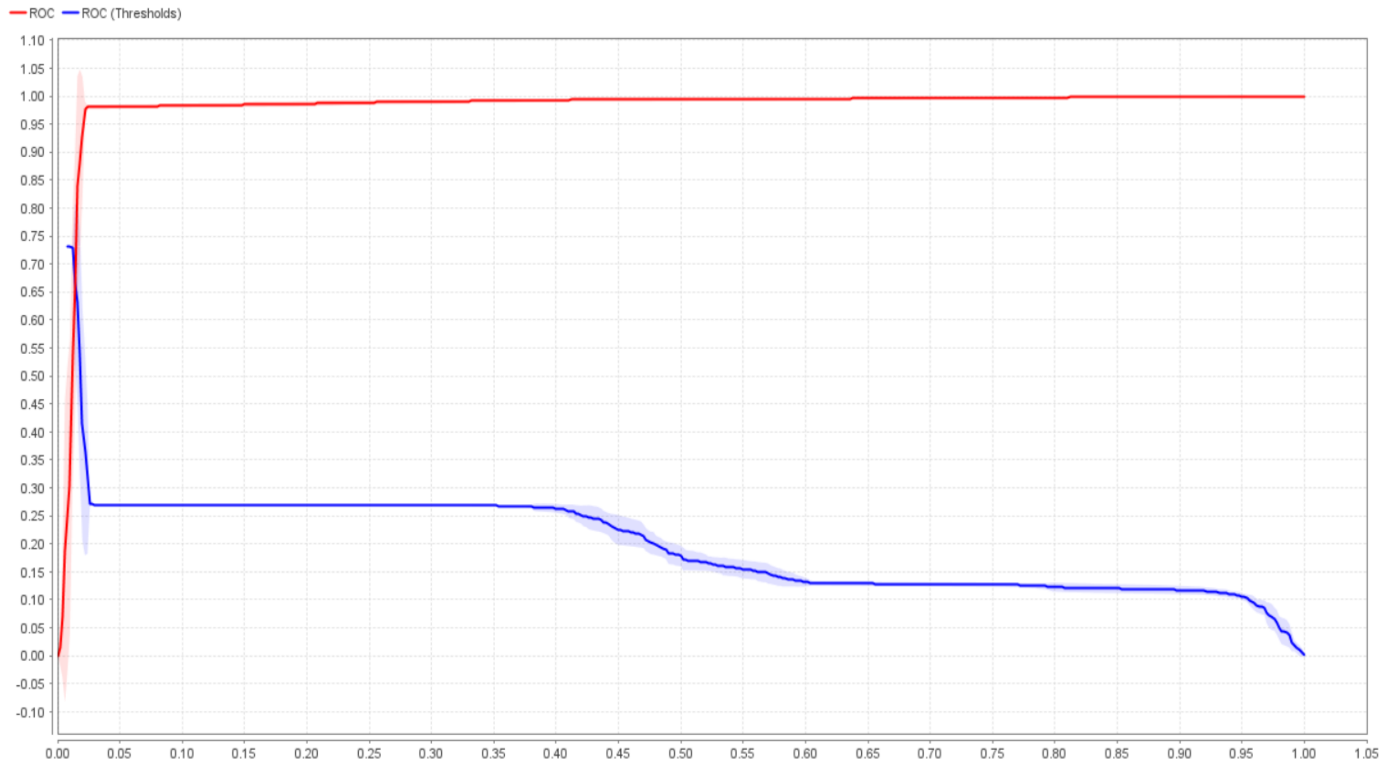

Fig. 5. ROC-curve machine-learning model (positive class: 0)

The proposed model was developed on the basis of real criminal records of 12,000 convicts in Ukraine. The input attributes are the following individual characteristics of prisoners that have the greatest impact on the propensity of convicts to commit repeat criminal offenses [7, 21]: age at the time of the first conviction to the actual degree of punishment, age at the time of the first conviction to the suspended or actual sentence, number of real convictions, number of suspended convictions, number of early dismissals. The constructed SVM classifier is of high quality and can be applied to new data sets to assess the risks of criminal recidivism and provide reliable decision - support for criminal enforcement.

Conclusion

Law enforcement agencies in developed countries are intensively using scientific methods and analytical tools to improve the efficiency of crime detection and effective crime prevention. Machine learning algorithms are used to predict the likelihood of future criminal offenses, identify individual characteristics of individuals that predispose them to repeat criminal offenses, identify interdependencies in criminal records, etc. However, such studies are difficult, as a crime in each country has its characteristics, depending, among other things, on legislation and mentality. In addition, crime is constantly changing. The development of information technology leads to the emergence of new types of crimes, changes the way they are committed and solved, and forms a new criminal consciousness. Such dynamic changes require a quick response from law enforcement agencies. For Ukraine, which is involved in a full-scale war against which convicts are also fighting, the problem of identifying persons prone to criminal recidivism is urgent.

The essence of the crime, as well as the generalized "portrait of a criminal" from around the world, have much in common. However, it is important to create individual criminal profiles, as well as to identify national characteristics of crime. This article is part of a series of works on the use of computational methods and mathematical modelling to develop a judicial information system for decision support in Ukraine. We have used one of the machine-learning algorithms to assess the risk of recidivism of criminal offenses by persons who have already been convicted of a criminal offense in the past. The model was trained using the criminal records of 12,000 convicted persons serving their sentences in Ukrainian penitentiaries. The SVM algorithm demonstrated high accuracy - the share of cases identified by the classifier as positive (which are positive) is 98.67%. The share of positive class objects out of all positive class objects identified by the classifier is 97.53%. The AUC is 0.981, which is very close to 1. The created SVM model can be applied to the new data set to predict the probability of criminal recidivism by convicts in the future and become part of a judicial information system for decision support.

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