Informatyka techniczna i sztuczna inteligencja
Technical informatics and Artificial Intelligence
Engineer of XXI Century'2024

Using machine learning models to decision-making in the justice system

Olha Kovalchuk [1], Ruslan Shevchuk [2,*], Nataliia Chudyk [1], Roman Ivanytskyi [3]

[1] Department of Law Theory and Constitutionalism, West Ukrainian National University, 46009 Ternopil, Ukraine, o.kovalchuk@wunu.edu.ua ; n.chudyk@wunu.edu.ua
[2] Department of Computer Science and Automatics, University of Bielsko-Biala, 43-309 Bielsko-Biala, Poland \ Department of Computer Science, West Ukrainian National University, 46009 Ternopil, Ukraine, rshevchuk@ubb.edu.pl
[3] Department of Physics and Mathematics, Ternopil Volodymyr Hnatiuk National Pedagogical University, 46004 Ternopil, Ukraine, ivanytskyiroman@tnpu.edu.ua
* Ruslan Shevchuk, rshevchuk@ubb.edu.pl

Abstract: Information technologies play a crucial role in security policy in a modern digital society. The increase in the number of criminals and the expansion of the range of crimes committed by them, which is observed all over the world, poses serious risks to the personal safety of citizens, the internal security of the country, and international security. Identifying links between the individual characteristics of prisoners and their criminal recidivism can help solve serial crimes, develop new crime prevention strategies, and provide reliable support for public safety decisions.

The presented work is a part of research on the development of information and analytical support for decision-making systems in criminal justice. This document presents a new analytical approach to criminal profiling. It is a case study of a unique real-world dataset of 13,010 criminal convicts. The k-means clustering technique was used to determine significant indicators (individual characteristics of prisoners) determining convicts' propensity to commit repeated criminal offenses. The built clustering model makes obvious the connection between the propensity for criminal recidivism and the following elements of the criminal profile: the number of previous convictions, the age at the time of the first conviction, the presence of conditional convictions, and early releases. The developed models can be applied to new criminal convicted datasets. The dynamic interaction of information technology and the criminal justice system will help reduce crime and strengthen internal security

Keywords: decision-making support; machine learning; criminal profiling; k-means clustering; recidivism; analytical support

Zastosowanie modeli uczenia maszynowego w procesie podejmowania decyzji sądowych

Olha Kovalchuk [1], Ruslan Shevchuk [2,*], Nataliia Chudyk [1], Roman Ivanytskyi [3]

[1] Katedra Teorii Prawa i Konstytucjonalizmu, Zachodnioukraiński Uniwersytet Narodowy, 46009 Tarnopol, Ukraina, o.kovalchuk@wunu.edu.ua ; n.chudyk@wunu.edu.ua
[2] Katedra Informatyki i Automatyki, Uniwersytet Bielsko-Bialski, 43-309 Bielsko-Biała, Polska \ Katedra Informatyki, Zachodnioukraiński Uniwersytet Narodowy, 46009 Tarnopol, Ukraina, rshevchuk@ubb.edu.pl
[3] Katedra Fizyki i Matematyki, Tarnopolski Narodowy Uniwersytet Pedagogiczny im. W. Hnatiuka, 46004 Tarnopol, Ukraina, ivanytskyiroman@tnpu.edu.ua
* Ruslan Shevchuk, rshevchuk@ubb.edu.pl

Streszczenie: Technologie informacyjne odgrywają kluczową rolę w polityce bezpieczeństwa w nowoczesnym społeczeństwie cyfrowym. Wzrost liczby przestępców i rozszerzenie zakresu przez nich popełnianych przestępstw, obserwowany na całym świecie, stanowi poważne zagrożenie dla bezpieczeństwa osobistego obywateli, bezpieczeństwa wewnętrznego kraju i bezpieczeństwa

DOI: https://doi.org/10.53052/9788367652292.03

międzynarodowego. Identyfikacja powiązań między indywidualnymi cechami więźniów a ich powrotem do przestępstwa może pomóc w rozwiązywaniu przestępstw seryjnych, opracowywaniu nowych strategii zapobiegania przestępczości i zapewnieniu wiarygodnego wsparcia dla decyzji dotyczących bezpieczeństwa publicznego.

Przedstawiona praca jest częścią badań nad rozwojem informacyjno-analitycznego wsparcia systemów decyzyjnych w sprawach karnych. Niniejsza praca przedstawia nowe podejście analityczne do profilowania przestępców. Jest to studium przypadku unikalnego, rzeczywistego zbioru danych dotyczącego 13 010 skazanych przestępców. Technika grupowania k-średnich została wykorzystana do określenia istotnych wskaźników (indywidualnych cech więźniów), determinujących skłonność skazanych do popełniania powtarzających się przestępstw. Zbudowany model grupowania ujawnia związek między skłonnością do powrotu do przestępstwa a następującymi elementami profilu przestępcy: liczbą wcześniejszych wyroków, wiekiem w momencie pierwszego skazania, obecnością warunkowych wyroków i wcześniejszych zwolnień. Opracowane modele mogą być stosowane do nowych zbiorów danych dotyczących skazanych przestępców. Dynamiczna interakcja technologii informacyjnych i systemu sądowego pomoże zmniejszyć przestępczość i wzmocnić bezpieczeństwo wewnętrzne.

Słowa kluczowe: wspomaganie podejmowania decyzji; uczenie maszynowe; profilowanie kryminalne; grupowanie k-średnich; recydywa; wsparcie analityczne

1. Introduction

The efficiency of the internal security system is an integral aspect of the country's external security, international security in general and attracts the attention of many politicians and officials. The effectiveness of the criminal justice system is increasingly the subject of discussion in academic circles. The justice of legal decisions is causing more and more disputes in society, as a part of the judicial system is under pressure from the government and politics. Thus, as the number of prisoners grows rapidly, it is logical that the police and justice authorities increasingly use decision-support systems to support decision-making processes. A decision support system (DSS) is an interactive computer system designed to support various activities when making decisions on unstructured and semi-structured decision problems. Such a system has the ability to work with interactive requests [1].

Most decision support systems, used in criminal justice (decision support systems in justice, DSSJ), are based on machine learning systems that use algorithms capable of learning from previous data and making predictions [2]. This increases the predictive probability of committing repeated criminal offenses, which is much more effective than the analysis of significant factors affecting the propensity of criminals to recidivism in each individual case. In addition, such computer algorithms are devoid of bias and subjectivity. Information systems that use such algorithms can provide reliable support for decision-making regarding the assessment of the risks of committing repeated criminal offenses by individuals and contribute to the improvement of the effectiveness of intelligent policing.

With the increase in the range of tasks that are solved with the help of DSSJ, the requirements for their use are increasing. Information technologies are constantly being improved. However, their application to support the decision-making process concerning the safety of the individual and society, the freedom and even the life of a person who may be falsely accused, imposes high requirements on the accuracy, reliability, and transparency of algorithms. The results of using such computer models should be comparable and verified on a large number of cases. The use of decision-making systems in the criminal justice system should help reduce the level of crime, and increase the level of personal safety of citizens and the safety of society.

1.1. Literature Review

The effectiveness of the use of DSS, and computer technologies, in particular big data and machine learning, in policing and the criminal justice system is one of the important and debatable topics in scientific literature today. B. Simmler studied the degree of distribution, implementation possibilities, technical features, institutional implementation and psychological aspects of the use of algorithms in the criminal justice system on the example of Switzerland [3]. O. Doyle studied the issue of efficiency in applying the DSS for reducing crime [4]. A. Završnik studied the influence of big data, algorithmic analytics, and machine learning tools on knowledge production in criminal justice settings [5]. B. Benbouzid conducted a detailed analysis of the content of predictive policing applications [6]. R. Berk assessed the risks of using artificial intelligence in law enforcement agencies [7]. S. Brayne studied the problems of using big data by law enforcement agencies [8]. M. Cavelty reviewed various analytical tools used in Switzerland to identify the recursive and non-linear relationship between security policy and technologies such as predictive policing, artificial intelligence and spyware [9]. S. Egbert et al investigated crime forecasting technologies based on data analysis and algorithmic detection of patterns, which are used to prevent criminal offenses as elements of preventive strategies in German-speaking countries [10]. A. Sandhu and P. Fussey analyzed the advantages of predictive policing, focused on the automation of police decisions, and the ability of predictive computer software to neutralize the subjectivity of police work [11]. B. Cheng et al. applied the FP-growth algorithm to find association rules between criminals and innocent people to identify persons suspected of crimes. [12]. K. Kotsoglou et al. investigated the possibilities of automated facial recognition for identifying suspects to facilitate the detection of crimes and eliminate false convictions [13]. A. Rummens et al. evaluated the effect of changing the spatio-temporal parameters of the predictive police model on the effectiveness of crime prediction based on data on apartment burglaries in a large city in Belgium [14]. M. Simmler et al. presented and discussed recommendations for assessing the usefulness and legitimacy of technical innovations in the criminal justice system [15]. P. Ugwudike conducted a critical analysis of the relationship between race and the use of risk prediction technologies in justice systems in Western jurisdictions such as the UK and the USA. [16]. F. Miro-Llinares established that the complexity of an algorithmic tool can cause misunderstanding of the decision-making process by users [17]. R. Yu et al. used longitudinal conviction data from district courts and assessed recidivism rates among individuals released from Swedish prisons in three security levels [18].

The use of a DSSJ has both advantages and disadvantages, which have not yet been sufficiently explored in scientific and legal circles. In addition, each country has specific features of development, validation, and use of DSS for the implementation of smart policing and smart criminal justice. In Ukraine, the implementation of the concept of implementing complex DSS for criminal justice is only at the stage of development and testing. Therefore, complex, multifaceted research in this field at the national level is expedient.

The machine learning models (Generalized Linear Model, Deep Learning, Decision Tree, Random Forest, Gradient Boosted Trees, and Support Vector Machine) were built to predict the propensity of convicts to commit criminal recidivism. It was found that the presence of conditional convictions and the number of convictions to the actual punishment are significant factors that affect the tendency of customers of penitentiary institutions to commit repeated criminal offenses in the future. Decision Trees models for the classification of convicts into "prone" and "non-prone" to recidivism were built [19].

The scoring model was created to assess the risk of repeated criminal offenses by convicts based on their individual statistical and dynamic characteristics. An optimal model based on Machine Learning systems was built to determine important factors that influence the propensity of convicted criminals to repeat criminal offenses and prisoners with a high level of recidivism [20]

The logistic regression model to predict the probability of convicted criminal recidivism in the future was built based on the analysis of individual characteristics of prisoners. It has been proven that age at the time of the first conviction, type of employment at the time of conviction, number of suspended convictions, number of minor crimes, number of crimes of medium gravity, and availability of early dismissals are determinants of the propensity of prisoners to criminal recidivism [21].

Applied the associative rule mining for the extract correlations and co-occurrences between the historical crime information of convicted. An associative rule mining model was built to search for non-obvious interesting connections between historical crime information of convicted and repeated offenses. The frequent item sets, which are combinations of individual characteristics of prisoners who commit criminal recidivism, and the strong association rules have been revealed. It was established that early dismissals and suspended convictions are the significant factors that cause the risk of recidivism [22-23].

Using the statistical survival analysis we computed the probability of the accused confessing to the commission of a criminal offense at a specific stage of the duration of the investigation. Assessment and forecasting of the risks of admitting guilt in committing criminal offenses under conditions of incomplete data were carried out. The Kaplan-Meier model was built for calculating the chances of obtaining evidence of a confession after the end of the trial in criminal proceedings. Created the Cox regression model to establish the relationship between the stages of the pre-trial investigation, at which the accused gives a confession, with the duration of the investigation and the method of prosecution (a crime committed by one person or a crime committed by a group of persons) [24-25].

The formation of reliable information and analytical support for complex DSSJ requires multi-faceted research and the construction of various effective models, the results of which confirm previously obtained assessments.

1.2. Organization

The rest of the paper is organized as follows. Section 2 presents a case study analyzing the characteristics of criminal convicts in Ukraine. The results of the analysis of the data on convicted individuals, which were used to construct a model that allows for the identification of factors influencing the propensity for recidivism, are presented in Section 3. Section 4 summarizes the content of the paper.

2. Materials and Methods

This research paper adopts a multidisciplinary approach, leveraging machine learning algorithms and their application in predicting recidivism hazards. It aims to address the need for novel methods in assessing parole and probation risks, determining optimal terms of imprisonment, and evaluating a defendant's threat level to society. This paper continues a series of multidisciplinary studies on utilizing machine learning to develop reliable information support for court decisions.

This study is based on a comprehensive case study utilizing a unique real-world dataset consisting of 13,010 criminal convicts. The dataset includes both static and dynamic characteristics of individuals who were serving sentences in penitentiary institutions across Ukraine.

The data used in this study covers a wide range of attributes, such as age, gender, education, employment status, previous convictions, and release conditions. These variables offer valuable insights into the socio-demographic, behavioral, and criminal profiles of the convicts. This kind of multifaceted data is crucial for building predictive models that can identify individuals at a higher risk of reoffending, thus contributing to more effective crime prevention strategies.

A significant portion of the dataset focuses on dynamic characteristics, such as the age at which individuals were first convicted and whether they had suspended sentences or early dismissals. These dynamic features are essential for understanding how criminal behavior evolves over time and how different life events influence the likelihood of reoffending. Additionally, the dataset includes key socio-demographic factors such as marital status, education level, and place of residence, which have been shown in previous research to correlate with criminal behavior.

The detailed attributes of the dataset are presented in Table 1 below, offering a comprehensive view of the variables considered in this study.

Table 1. The crime records data

Attribute	Value	Meaning
Recidivism	1	yes
	0	no
Sex	1	male
	2	female
Age	1	to 18 years
	2	from 18 to 30 years
	3	from 30 to 45 years
	4	older than 45 years
Age1 (age at the time of the first conviction (to the actual degree of punishment))	1	to 18 years
	2	from 18 to 30 years
	3	from 30 to 45 years
	4	older than 45 years
Age2 (age at the time of the first conviction (conditional or actual sentence))	1	to 18 years
	2	from 18 to 30 years
	3	from 30 to 45 years
	4	older than 45 years

Marital status	1	single
	2	married
Education	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)	0	rural area
	1	urban area
Type of employment (type of employment at the time of conviction (up to actual punishment))	0	unemployed
	1	part-time
	2	full-time
Early dismissals (availability of early dismissals)	0	no
	1	yes
Motivation for dismissal	0	no
	1	yes
Suspended convictions	number of suspended convictions	

The data has been carefully curated and cleaned to ensure accuracy and consistency across all variables. We used the k-means clustering algorithm to segment the convicts into distinct groups based on their propensity for recidivism. This method allowed us to identify significant indicators (e.g., number of previous convictions, age at first conviction) that are associated with a higher likelihood of reoffending.

3. Results

3.1. Criminal profiling strategy

One of the decision-support strategies in criminal proceedings is criminal profiling [26]. A criminal profile is a set of conclusions about the qualities of a person responsible for committing a crime or a series of crimes. To date, there is no single effective method of forming accurate, substantiated conclusions regarding criminal profiling. In this work, we used one of the methods of intelligent data analysis to create typical criminal profiles of convicts. The k-means method [27] was used for clustering convicts (distribution into relatively homogeneous groups) according to their individual characteristics. The empirical analysis was carried out in the RapidMiner predictive analytics environment [28]. To create a cluster model, a process consisting of operators is presented in Fig. 1–3 and Tables 2–4.

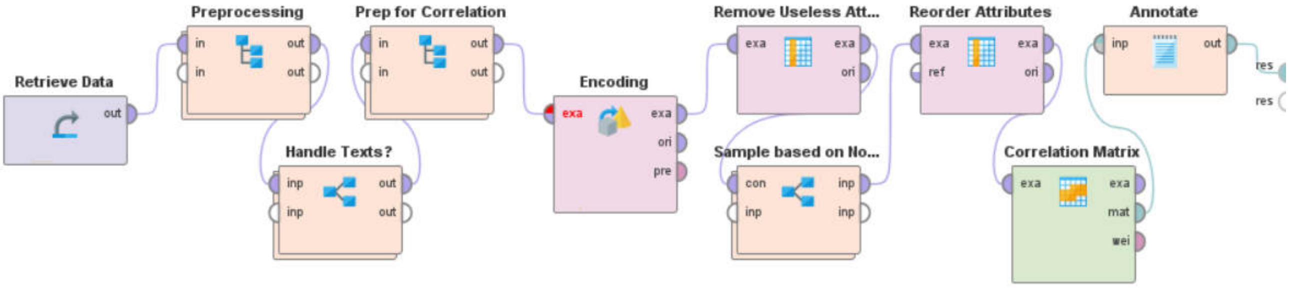

Figure 1. Operators of the process of creating a cluster model for dividing convicts into groups based on similar individual characteristics

Table 2. K-means clustering process operates

Operator	Description
Retrieve data	Loads a RapidMiner object (dataset) into the process
Preprocessing	Introduces a process subprocess (chain of operators that will be applied later) within a process
Handle text?	The root operator "Should handle text columns?" is the outermost operator of every process
Prep for correlation	Prepares dataset for correlation calculation
Encoding	Performs one-hot encoding on the data and removes columns with too many nominal values
Remove Useless Attributes	Removes useless columns like constants
Sample-based on No Attributes	Samples data down based on the number of attributes
Recorder Attributes	Orders columns alphabetically
Correlation Matrix	Creates the actual correlation matrix
Annotate	Defines a result name

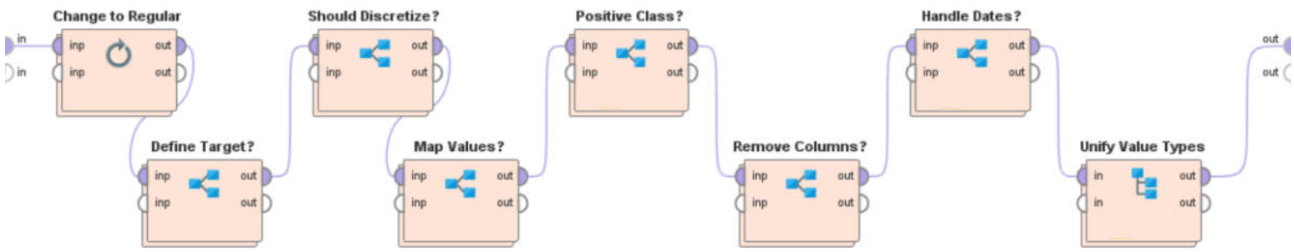

Figure 2. Preprocessing operators

Table 3. Nested statements of the preprocessing

Operator	Description
Change to Regular	Changes the role to 'regular' for all columns.
Define Target	Selects Subprocess
Should Discretize?	Introduces a process within a process
Map Values	Switches options
Positive Class?	Consists of the nested operators: Nominal to Binominal, which changes the type of selected nominal attributes to a binominal type, and Define Positive Class, which modifies the internal value mapping of binominal attributes according to the specified negative and positive values
Remove Columns	Consists of the nested operator Remove Columns, which removes columns
Handle Dates	Consists of the nested operator Remove Dates
Unify Value Types	Consists of the nested operators: Remove Unused Values, which removes all unused values and orders the value mappings alphabetically; Nominal to Text, which transforms all nominal columns to text; Text to Nominal, which transforms all text columns into polynomial columns; Numerical to Real, which turns all numerical columns; Set Text Column, which defines the value type of all texts column

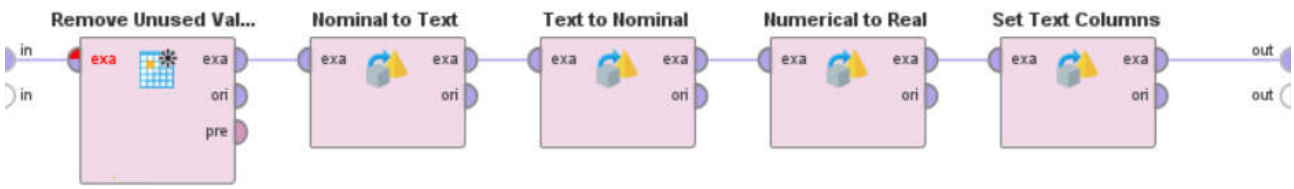

Figure 3. Preprocessing: Unify Value types

Table 4. Nested statements of the Unify Value Types Operator

Operator	Description
Remove Unused Value	Removes each nominal value that is not assigned to an example
Nominal to Text	Changes the type of selected nominal attributes to text
Text to Nominal	Changes the type of selected text attributes to nominal
Numerical to Real	Changes the type of the selected numerical attributes to the real type
Set Text Columns	Sets text columns

3.2. Experiments

Two clusters of convicts were identified, which included 6,266 and 6,744 people, respectively (Fig. 4, 5). The Real convictions and Early dismissals attributes had the greatest influence on the formation of cluster 0, and the Recidivism attribute (the presence of criminal recidivism) on the formation of cluster 1.

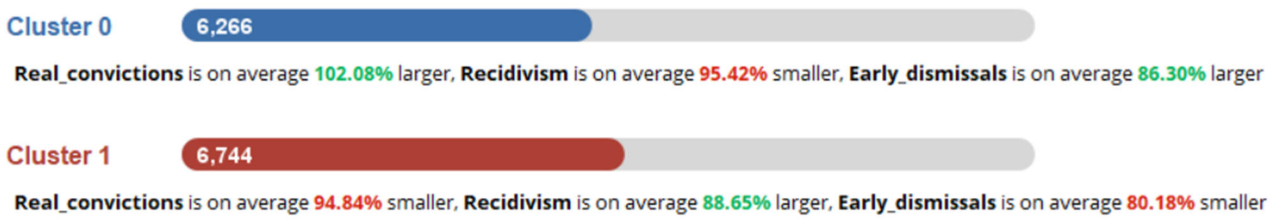

Figure 4. K-means summa

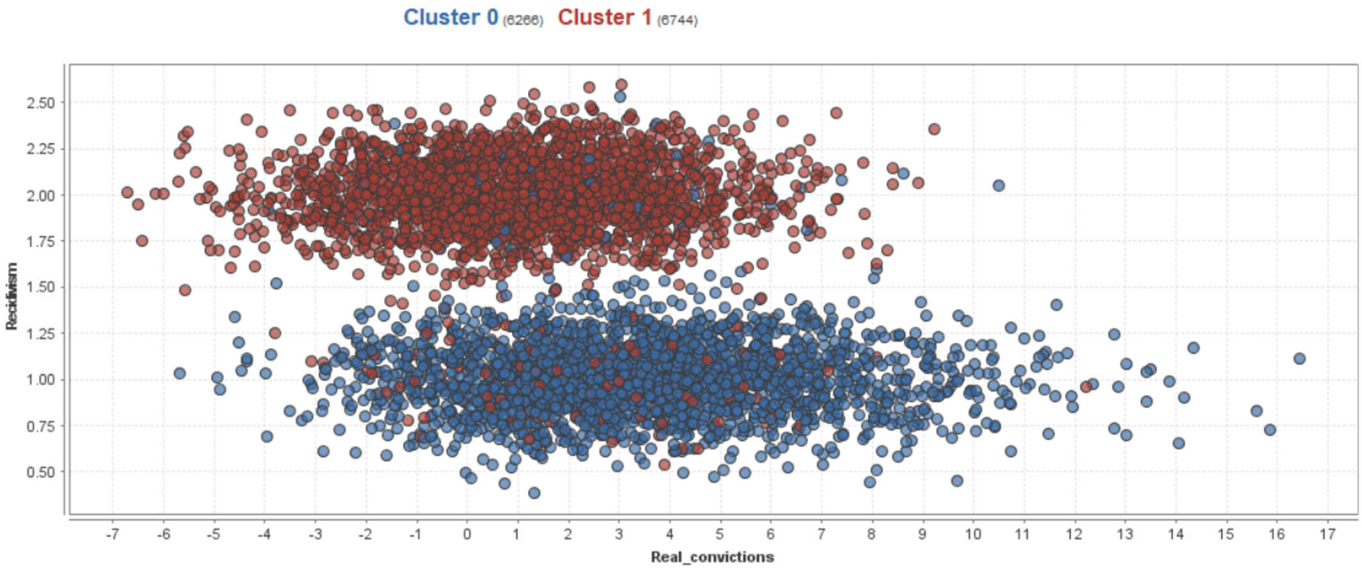

Figure 5. Scatter Plot

The average values of the analyzed attributes (centroids) were calculated for each of the selected clusters of convicts (Table 5). Cluster 0 includes criminals who committed twice as many (on average) repeated criminal offenses as those convicted from Cluster 1. Criminals from cluster 0 committed a first crime and were convicted for the first time (on average) at an earlier age than prisoners, who make up cluster 1. Convicts who formed cluster 0 served (on average) three times more actual sentences compared to individuals from cluster 1. Almost twice as many (on average) suspended sentences were given to prisoners included in cluster 0 than to convicts from cluster 1.

Table 5. Centroid table (fragment)

Cluster	Age	Age1	Age2	Early dismissals	Motivation for dismissal	Real convictions	Recidivism	Suspended convictions
Cluster 0	3.14	1.86	1.72	0.55	0.85	3.48	1.02	0.08
Cluster 1	3.92	2.52	2.42	0.06	0.90	1.06	1.06	0.50

The graph of cluster averages (Fig. 6) gives reason to conclude that the biggest differences between the selected groups of convicts are observed among the average values of the following attributes: Real convictions (number of convictions before the actual punishment), Recidivism (presence of relapses), Age1, Age2 (age at the time of the first convictions to the actual and conditional sentence), Suspended convictions (the presence of conditional convictions) and Early dismissals (the presence of early dismissals). The obtained results give an idea of the regularities revealed between the analyzed individual characteristics of criminals.

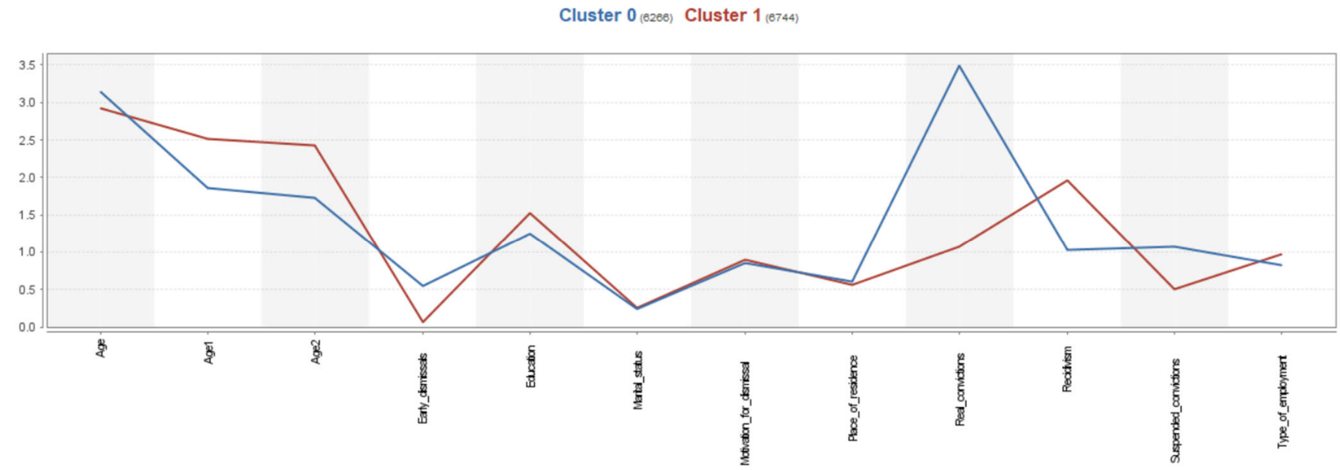

Figure 6. K-means centroid chart

A correlation matrix was constructed to assess the relationships between the investigated features (Table 6). The Recidivism attribute has the strongest correlations with Early dismissals (0.41), Age2 (0.39) and Age1 (0.38). Therefore, it can be argued that early release and age at the time of the first conviction (both before actual and conditional punishment) are risk factors for convicts committing new criminal offenses.

Table 6. Correlation table (fragment)

Attributes	Age	Age1	Age2	Early dismissals	Motivation for dismissal	Real convictions	Recidivism	Suspended convictions
Age	1	0.37	0.35	0.14	-0.01	3.48	0.25	0.08
Age1	0.37	1	0.88	-0.22	0.06	1.06	1.06	0.50
Age2	0.35	0.88	1	-0.23	0.05	-0.35	0.40	-0.22
Early dismissals	0.14	-0.22	-0,23	1	0.02	0.41	-0.50	0.19
Motivation for dismissal	-0.00	0.06	0.01	0.02	1	-0.08	0.08	0.00
Real convictions	0.25	-0.36	0.41	0.41	-0.08	1	-0.68	0.12
Recidivism	-0.2	0.38	-0.40	-0.50	0.08	-0.68	1	-0.19
Suspended convictions	-0.00	-0.13	-0.22	0.19	0.00	0.12	-0.19	1

To simplify the understanding of the algorithm for the distribution of convicts into selected clusters based on the analyzed attributes, a decision tree for the cluster model was built (Fig. 7).

The results of the built machine learning and artificial intelligence cluster model confirmed the estimates obtained in previous works of this series. The penitentiary system does not perform a correctional function yet. Rather, the opposite is true: the earlier a person enters correctional institutions for the first time, the more likely he is to re-offend. However, the chance for correction provided by the judicial system in the form of conditional convictions and early releases also provokes relapses in most cases.

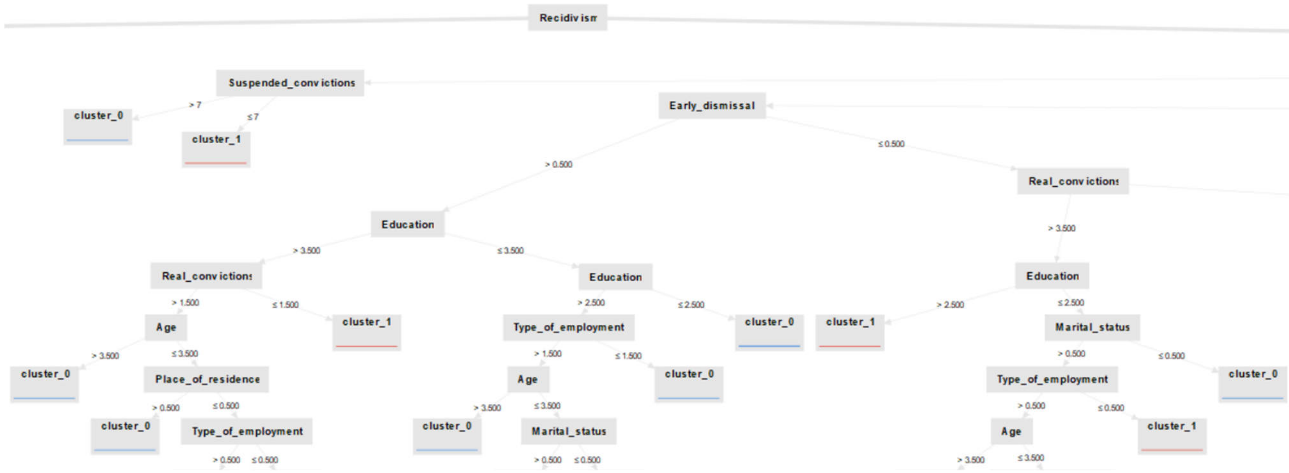

Figure 7. Cluster Tree (fragment)

4. Conclusions

Criminal offenses pose a significant threat to Ukraine's internal security. The study of individual characteristics of criminals, which are risk factors for criminal recidivism, requires special attention. The public danger is not the fact of committing a repeated offense, but the personal qualities of the criminal. Identifying links between the individual characteristics of prisoners and their criminal recidivism can help solve serial crimes, develop new crime prevention strategies, and provide reliable support for public safety decisions. In the context of Russia's war against Ukraine, the problem of crime poses a serious challenge to Ukraine's external security, since a significant proportion of those mobilized into the Russian army are prisoners. They commit repeated crimes already on the territory of Ukraine. Criminal profiling does not provide unequivocal indisputable evidence to solve a criminal case, but it is an effective tool in the investigation of serial crimes, hostage taking, rape, and sexual murders and in establishing the authorship of texts, such as threatening letters.

It is a case study of a unique real-world dataset of 13,010 criminal convicts. We applied the Rapid Miner tool to the machine learning k-clustering algorithm and built a cluster model. The relationship between the number of previous convictions of prisoners, the age at the time of the first conviction, the presence of conditional convictions, and early releases with the risk of criminal recidivism in the future has been proven. The built computer model makes obvious the relationship between the fact of criminal recidivism and the elements of the profile of the criminal (individual characteristics of the person), providing reliable support when making decisions in criminal proceedings. The obtained results confirmed the estimates obtained at the previous stages of a series of studies on the application of quantitative tools and the construction of computer models for the development of informational and analytical support of the decision-making in criminal justice, to simplify the understanding of criminal behavior and to provide effective support for judicial decision-making. The models of computation developed in this series can be applied to new criminal convicted datasets and become the basis for the formation of information and analytical support for complex DSS and provide reliable information support when making effective decisions in criminal proceedings and developing effective strategies for crime prevention and ensuring internal security.

References

1. Blokdyk G. Decision Support System. A Complete Guide. Publisher: 5STARCooks. 2020. URL: https://www.scribd.com/book/426601046/Decision-Support-System-A-Complete-Guide-2020-Edition (accessed: 04.10.2024).
2. Reforming Benefits Decision-Making. A Report by Justice and the Administrative Justice Council. Carter Lane. London. 2021. URL: https://justice.org.uk/wp-content/uploads/flipbook/50/book.html (Last accessed: 22.01.2023).
3. Simmler M., Brunner S., Canova G., et al. Smart Criminal Justice: exploring the use of Algorithms in the Swiss Criminal Justice System. *Artif Intell Law*. 2022. Vol. 31. Pp. 213–237. https://doi:10.1007/s10506-022-09310-1.
4. Doyle O. The Role of Decision Support Systems in the Criminal Justice System. Department of Political Science. 2020.

5. Zavrsnik, Algorithmic justice: algorithms and big data in criminal justice settings. *Eur J Criminol*. 2019. Vol. 18(35). https://doi:10.1177/1477370819876762.
6. Benbouzid, To Predict and to Manage: Predictive Policing in the United States. Big Data Soc. 2019. Vol. 6(1). Pp. 1–13. https://doi:10.1177/2053951719861703.
7. Berk R. A. Artificial Intelligence. Predictive Policing, and Risk Assessment for Law Enforcement. *Ann Rev Criminol*. 2021. Vol. 4(1). Pp. 209–237. https://doi:10.1146/annurev-criminol-051520-012342.
8. Brayne S. Predict and Surveil: Data, Discretion, and the Future of Policing. Oxford University Press. 2021. https://doi:10.1093/oso/9780190684099.001.0001.
9. Cavelty M. D., and Hagmann J. The Politics of Security and Technology in Switzerland. *Swiss Political Sci Rev*. 2021. Vol. 27(1). Pp. 128–138. https://doi:10.1111/spsr.12430.
10. Egbert S., and Krasmann S. 2020. Predictive Policing: Not Yet, but Soon Preemptive? *Policing and Society*. 2020. Vol. 30(8), Pp. 905–919. https://doi:10.1080/10439463.2019.1611821.
11. Sandhu A. The "Uberization of Policing"? How Police Negotiate and Operationalize Predictive Policing Technology. *Polic Soc*. 2021. Vol. 31(1). Pp. 66–81. https://doi:10.1080/10439463.2020.1803315.
12. Cheng W. Li., Tong H. Prediction of Criminal Suspects Based on Association Rules and Tag Clustering. *Journal of Software Engineering and Applications*. 2019. Vol. 12(3). Pp. 35–50. https://doi:10.4236/jsea.2019.123003.
13. Kotsoglou K. N., Oswald M. The Long Arm of the Algorithm? Automated Facial Recognition as Evidence and Trigger for Police Intervention. *For Sci Int Synergy*. 2020. Vol. 2. Pp. 86–89. https://doi:10.1016/J.FSISYN.2020.01.002.
14. Rummens A, Hardyns W. The Effect of Spatiotemporal Resolution on Predictive Policing Model Performance. *Int J Forecast*. 2021. Vol. 37(1). Pp. 125–133. doi: 10.1016/j.ijforecast.2020.03.006.
15. M. Simmler, G. Canova, and K. Schedler, Smart Criminal Justice: Phenomena and Normative Requirements. Int Rev Admin Sci, 2021. https://doi:10.1177/00208523211039740.
16. Ugwudike P., Digital Prediction Technologies in the Justice System: the Implications of a 'Race-Neutral' Agenda. *Theor Criminol*. 2020. Vol. 24(3), Pp. 482–501.
17. F. Miro-Llinares F., Predictive Policing: Utopia or Dystopia? On Attitudes Towards the Use of Big Data Algorithms for Law Enforcement. *Idp-Internet Law Polit*. 2020. Vol. 30. Pp. 1–18. https://doi:10.7238/idp.v0i30.3223.
18. Yu R., Långstro N., Forsman M., Sjo A., Fazel S., Molero Y. Associations between prisons and recidivism: A nationwide longitudinal study. *PLoS ONE*. 2022. Vol. 17(5):e0267941. https://doi:10.1371/journal.pone.0267941.
19. Kovalchuk O., Karpinski M., Banakh S., Kasianchuk M., Shevchuk R., and Zagorodna N., Prediction Machine Learning Models on Propensity Convicts to Criminal Recidivism. *Information*. 2023. Vol. 14(3). P. 161. https://doi:10.3390/info14030161.
20. Kovalchuk O., Banakh S., Masonkova M., Burdin V., Zaverukha O., and Ivanytskyy R. A Scoring Model for Support Decision Making in Criminal Justice. *In Proceedings of the 12th International Conference on Advanced Computer Information Technologies (ACIT-2022)*. IEEE, Ruzomberok, Slovakia. 2022. Pp. 116–120. https://doi:10.1109/ACIT54803.2022.9913182.
21. Berezka K. M., Kovalchuk O. Ya., Banakh S. V., Zlyvko S. V., and Hrechaniuk R. A Binary Logistic Regression Model for Support Decision Making in Criminal Justice. *Folia Oeconomica Stetinensia*, 2022. Vol. 22 (1). Pp. 1–17. https://doi:10.2478/foli-2022-0001.
22. Kovalchuk O., Banakh S., Kasianchuk M., Moskaliuk *N., and Kaniuka V. Associative Rule Mining for the Assessment of the Risk of Recidivism. In Proceedings of the 4th International Workshop on Intelligent Information Technologies & Systems of Information Security (IntelITSIS 2023).* CEUR Workshop Proceedings, Khmelnytsky, Ukraine. 2023. Vol. 3373. Pp. 376–387. URL: https://ceur-ws.org/Vol-3373/.
23. Kovalchuk O., Kasianchuk M., Karpinski M., Shevchuk R. Decision-Making Supporting Models Concerning the Internal Security of the State. *International Journal of Electronics and Telecommunications*. 2023. Vol. 69(2). P. 301–307. https://doi:10.24425/ijet.2023.144365.
24. Kovalchuk O., Kolesnikov A., Koshmanov M., Dobrianska N., Polonka I. Rethinking the Concept of Punishment: Modeling the Level of Danger Posed by Criminals to Society. *Amazonia Investiga*. 2024. Vol. 13(77). Pp. 246–256. https://doi:10.34069/AI/2024.77.05.18.
25. Kovalchuk O., Shevchuk R., Babala L., Kasianchuk M. Support vector machine to criminal recidivism prediction. *International Journal of Electronics and Telecommunication*. 2024. Vol. 70(3). P. 691–697. DOI: https://doi:/10.24425/ijet.2024.149598.

26. Petherick W., and Brooks N. Reframing Criminal Profiling: a Guide for Integrated Practice. *Psychiatr Psychol Law*. 2020. Vol. 28(5). Pp. 694–710. https://doi:10.1080/13218719.2020.1837030.
27. Cluster Analysis. Science Direct. URL: https://www.sciencedirect.com/topics/medicine-and-dentistry/cluster-analysis (Last accessed: 13.09.2024).
28. RapidMiner Documentation. URL: https://docs.rapidminer.com (accessed: 03.09.2024).