INTL JOURNAL OF ELECTRONICS AND TELECOMMUNICATIONS, 2023, VOL. 69, NO. 2, PP. 301-307
Manuscript received December 11, 2022; revised April, 2023. DOI: 10.24425/ijet.2023.144365

Decision-Making Supporting Models Concerning the Internal Security of the State

Olha Kovalchuk, Mykhailo Kasianchuk, Mikolaj Karpinski, and Ruslan Shevchuk

Abstract—**In the digital society, states' information security has become one of the key elements of ensuring the competitiveness and sustainable development of the state, guaranteeing its integrity and security in general. An important component of state security is the internal security of the state, which must ensure the personal and public safety of its citizens. Modern Ukraine is building a new system of criminal justice, which requires a new information system for risk assessment and support for optimal decision-making. Today, applied research and the development of information and analytical software for the internal security of the state have acquired a special meaning.**

In the paper, there is built a set of models for providing operational information for decision-making in criminal justice. This is a cluster model for creating criminal profiles of convicts, and a scoring model for identifying individual characteristics of criminals that have the greatest impact on their propensity to re-offend. The obtained models can provide reliable support for decision-making in the field of criminal justice and become part of the information support system for the internal security of Ukraine in general.

Keywords—**information security of the state; decision-making; information and analytical support; internal security; model**

I. Introduction

INFORMATION security involves protecting information by reducing the consequences of information threats. In most cases, this issue is considered through the prism of cyber security, social networks, and fake news. However, the problem is much broader and more complex. Today's highly developed information society is increasingly exposed to various information threats that have consequences for all important spheres of social life. These are the economy, education, information technologies, ecology, culture, health care, international relations, internal and external security, and the image of the state. And all these areas require reliable information security and effective information and analytical support for decision-making. And in light of russia's great war against Ukraine, the scale of terrorist threats became more obvious, not only from individuals or terrorist groups but also at the state level. And all these areas require reliable information security and effective information and analytical support. An important component of state security is the internal security of the state. The personal safety of citizens and society, in general, depends on this subsystem. Ensuring the public safety of Ukraine today requires the use of effective risk management tools and models for informational and analytical decision-making support in the field of criminal justice.

According to the latest World Prison Brief estimates, dated December 2021, the number of prisoners worldwide is increasing every year and is more than 11.5 million. [1] Ukraine ranks 108th among the other 120 countries of the world in terms of the number of prisoners [2]. This is a much worse position than the countries of the European Union. This situation can be explained, in particular, by the fact that Ukraine has still not implemented the institution of probation, as in the EU. There is also an economic effect in this matter: it is always cheaper to socialize and control a person in society than to keep him in a penitentiary. The ratio of the cost of probation to the cost of imprisonment in European countries ranges from 1:10 to 1:25. In addition, passing a sentence that allows the convict to be a full member of society will mean that he will be able to provide not only for himself but also for his family. He will work for the country's economy and society. However, the priority criterion for probation measures remains safety. This is the personal safety of citizens and society in general. First of all the probation model should take into account all potential risks and have effective risk management tools. Therefore, today an urgent problem is the development of quality models that would provide reliable support in making effective decisions in criminal justice and become part of the information and analytical provision of Ukraine's internal security.

II. Related work

Applied research in the field of criminal justice, which would provide up-to-date important information when making decisions in the field of internal security, is at the initial stage of development and requires the creation of a reliable theoretical base and evaluation of its effectiveness using a strictly scientific method. Research by scientists in this area is based on the analysis of forensic and behavioral evidence and in many cases uses data analytics and computer modeling. F. Itulua-Abumere investigated the effectiveness of criminal profiling and predicted the characteristics of robbers based on separate empirical assessments of the criminal profile [3]. V. Tretynyk and A. Cherniavskyi developed a model of the psychological portrait of a criminal based on the rules of fuzzy logic [4]. K. Berezka and others built a predictive model for assessing the risks of criminal recidivism based on the analysis of convicts' individual characteristics [5]. A. Babuta, M. Oswald, and C. Rinik investigated the application of machine learning algorithms to support decision-making by law

Olha Kovalchuk and Mykhailo Kasianchuk are with West Ukrainian National University (e-mail: {o.kovalchuk, kmm}@wunu.edu.ua).
Mikolaj Karpinski are with University of Bielsko-Biala (e-mail: mkarpinski@ath.bielsko.pl).
Ruslan Shevchuk are with University of Bielsko-Biala and West Ukrainian National University (e-mail: rshevchuk@ath.bielsko.pl).

enforcement agencies, in particular regarding predictions of the propensity of individuals to future crimes [6]. M. Ghasemi et al. applied artificial intelligence algorithms for risk assessment during decision-making in criminal justice [7]. Yu. Rongqin. et al examined differences in recidivism rates between different prisons based on Cox proportional hazards regression and stratified Cox proportional hazards regression. They found that in predicting recidivism individual differences between convicts are more important factors [8]. E. F.J.C Van Ginneken and P. Nieuwbeerta explored the concept of prison climate and conducted empirical research on prison climate [9]. O. Kovalchuk et al. used the data mining model to analyze the risks of recidivism [10]. R. Berks used machine learning statistical procedures to forecasting criminal recidivism [11]. Mostly, researches are on various aspects of the economics of incarceration [12-17]. However, this area requires the use of various tools (statistical, mathematical, data mining, big data) for the development of reliable forecasting models and the formation of reliable information support for the country's internal security system.

III. Data Collection and Research Methodology

The task of applied research was to build qualitative models that would provide reliable support for decision-making in criminal justice and useful information for internal security agencies. In order to check the adequacy of the obtained results, several models were built: a cluster model to identify significant factors that would allow to determining the criminal profile of the criminal based on his individual statistical features and dynamic characteristics; a classification model based on binary logistic regression to classify convicts into relatively homogeneous groups in order to predict their propensity for future recidivism; a scoring model for determining significant factors affecting the propensity of convicts to repeat crimes. The data collection was formed on the basis of individual statistical data and dynamic characteristics of 13,010 convicts serving their sentences in the penitentiary institutions of Ukraine. The following nominal variables were used in conducting empirical research:

- Recidivism (the presence of recurrences): 0 – no,1 – yes;
- Sex: 1 – male, 2 – female;
- Age: 1 – up to 18 years, 2 –18-30 years; 3 – 30-45 years; 4 – older than 45 years;
- Age1 (age at the time of the first imprisonment): 1 – up to 18 years, 2 – 18-30 years; 3 – 30-45 years; 4 – older than 45 years;
- Age2 (age at the time of the first conviction): 1 – up to 18 years, 2 – 18-30 years; 3 –30-45 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.

Numerical variables:

- Number of minor children (number of minor children at the time of conviction (to the real extent);
- Real convictions (number of real convictions);
- Conditional convictions (number of conditional convictions);
- Minor crimes (number of minor crimes);
- Crimes of medium gravity (number of crimes of medium gravity);
- Serious crimes (number of serious crimes);
- Particularly serious crimes (number of particularly serious crimes).

Recidivism is the dependent variable, and the other – is the independent.

In order to create criminal profiles of criminals, it was used cluster analysis (the division of a set of elements into relatively homogeneous groups, or clusters). A criminal profile (profile of the criminal) is a set of conclusions about the qualities of a person responsible for committing a crime or a series of crimes. The strategy of criminal profiling is based on the intersection of science, logic and cognition [18]. A multidimensional grouping of objects (convicts) was carried out according to similar characteristics (statistical and dynamic characteristics. An important advantage of cluster analysis, along with other classic modeling methods, is the ability to divide objects not by one parameter, but by a certain set of features. Such research can be conducted for a set of initial data of an almost arbitrary nature. This is of great practical importance in the presence of heterogeneous indicators, which complicate the application of traditional mathematical approaches. Cluster analysis makes it possible to analyze sufficiently large volumes of data and sharply shorten, and compress large arrays of information, making them compact and visual. The solution to the classification problem is the assignment of each of the data objects to one (or several) of the predefined classes and the construction of a data model as a final result, which determines the division of a set of data objects into classes, using one of the classification methods [19].

The method of binary logistic regression was used in order to determine the possibility of applying a milder punishment (probation or parole) to the convicts. Convicts with a high risk of committing repeated criminal offenses were found among the analyzed sample. The method is based on predicting the probability that the defendant will commit a crime in the future and is intended to inform judges about the recommended length of the sentence. We used static risk factors, such as age at first arrest and gender, combined with dynamic risk factors, such as marital status, employment status, and education level, to derive a comparative risk score based on prior offender data.

The dependence of the binary variable (*Recidivism*) on several independent variables (nominal and numerical) is investigated.

A scoring model (weighted scorecard) was built to identify the individual characteristics of convicts, which determine their probable propensity to commit repeated criminal offenses [20]. It is a technique for weighing certain decisions. This mathematical model is used to prioritize strategies and decisions by assigning a numerical value. Scoring models are built by applying statistical methods (Chi-square test or ROCcurve) to the studied array of data (nominal and numerical features) in order to assess the risks of the occurrence of an event and find significant factors influencing the predicted probability of its occurrence.

To date, there is no one effective method of forming accurate, well-founded conclusions regarding the adoption of optimal decisions in criminal justice. Solving this problem requires multifaceted study and the use of a wide range of tools for the applied understanding of the logic of science and the search for optimal solutions for the internal security of the state. Applying the scientific method is the first of a series of steps that can neutralize the effects of even the most common subtle forms of bias, conscious or unconscious, that are distorted by context and the psychological state of the decision-maker. Analysis of empirical data using computer modeling tools is one of the reliable methods of obtaining objective conclusions.

IV. Empirical Results and Discussion

A. *A cluster model for criminal profiling*

One of the important areas of application of modeling in criminal justice is the creation of criminal profiles of criminals with the aim of establishing a probable correlation between demographic characteristics of the criminal, social status, education, marital status, statistical data on crimes, the length of the sentence served, previous criminal history, the presence of suspended sentences, early release, motivation to be released, etc. Criminal profiling is used when making decisions on issues where the cost of a mistake is a person's freedom or life, so it is important to choose a rational approach and maintain objectivity.

As a result of the application of the clustering tree (joining) and k-means methods, a mathematical model was obtained that determines the division of a set of data objects into classes (Fig. 1-2). 2 clusters are identified. The variable *Real convictions* have the greatest influence on the distribution of convicts into groups. It is the main indicator of a high probability of criminal recidivism. Important factors for predicting repeated crimes are minor crimes, serious crimes, and conditional convictions. Other analyzed indicators (marital status, education, place of residence, type of employment, motivation) do not differ significantly for convicts from different groups.

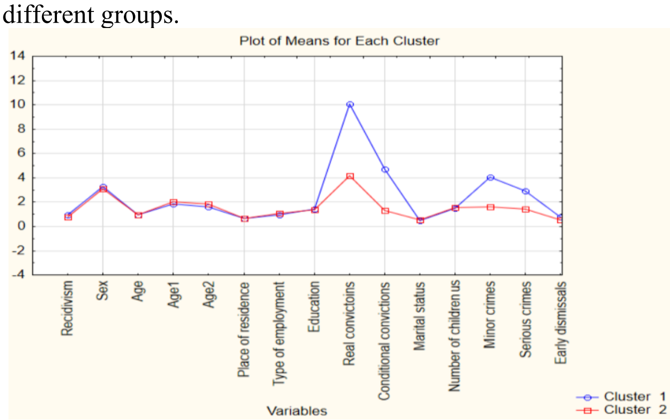

Fig. 1. Dendrogram

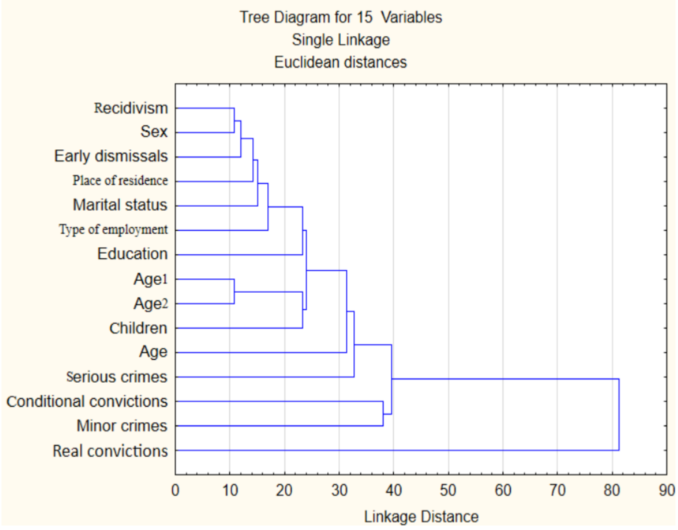

Fig. 2. Plot of means for each cluster

The first cluster included prisoners with a high risk of recidivism (on average 0.95), who received their first criminal record (prior to conditional or real terms of conviction) in adolescence or young adulthood (Table I). Most of them had, on average, at least four suspended sentences and were released early in three out of four cases.

Table I
Means of Variables for Objects of Selected Clusters

Variable	Cluster No. 1	Cluster No. 2
Recidivism	0.95455	0.7672
Age	3.30682	3.1187
Sex	0.95455	0.9239
Age1	1.81818	2.0403
Age2	1.61364	1.8384
Place of residence	0.65909	0.6389
Type of employment	0.97727	1.0498
Education	1.44318	1.3610
Real convictions	10.09091	4.1971
Conditional conviction	4.68182	1.2874
Marital status	4.04545	0.5083
Children	1.50000	1.5534
Minor crimes	4.04545	1.5938
Serious crimes	2.89773	1.4180
Early dismissals	0.76136	0,5344

The second cluster was formed by convicts with a slightly lower risk of recidivism (on average 0.77), most of whom were convicted for the first time (prior to conditional or real terms of conviction) in middle age.

The variables Real convictions (10 to 4), Minor crimes (4 to 1.6), Serious crimes (2 to 1), and Conditional convictions (respectively, on average 4.7 for objects of the first cluster and 1.3 for the second) have the best impact on the distribution of prisoners into clusters according to the propensity to commit repeated criminal offenses.

The conducted empirical analysis gives reason to conclude that the maximum influence on the probability of criminal recidivism is exerted by the following factors: number of real convictions, number of minor and serious crimes, and leniency of the judicial system towards persons who have committed a crime (presence of suspended convictions and early releases). Impunity often gives rise to a dubious sense of permissiveness, and "prison institutions" do not contribute to the unconditional correction of convicts. Therefore, the search for effective solutions that will ensure the safety of society and at the same time can contribute to the reduction of state costs for the maintenance of prisoners in penitentiary institutions, for example, by implementing a probation institute, is becoming more and more relevant.

B. Scoring Model for identifying the most significant characteristics of criminals that influence the propensity to recidivism

A Scoring model was built to identify individual characteristics of criminals, which are significant indicators of the propensity of convicts to criminal recidivism. For each prisoner, a "tendency" to recidivism is determined - a binary feature (Recidivism). This variable stores information about the probable "propensity" to commit repeated criminal offenses of each individual convict. In the studied dataset, 70% of convicts are classified as "prone" to recidivism, and 30% - as "not prone" to recidivism.

The significance table contains information about the most significant variables for building a predictive model (Table II).

Based on the table of the significance of independent variables for the dependent variable Recidivism, we draw conclusions about the discriminant weight of each of the predictors: the higher the rank of the corresponding predictor, the greater its significance.

TABLE II
PREDICTOR IMPORTANCE FOR DEPENDED VARIABLE RECIDIVISM

Variable	Importance
Number of conditional convictions	1.00
Number of particularly serious crimes	0.41
Age at the time of the first conviction (to the actual degree of punishment)	0.39
Availability of early dismissals	0.26
Age at the time of the first conviction (conditional or actual sentence)	0.25
Sex	0.25
Education	0.09
Marital status	0.07
Type of employment (up to actual punishment)	0.04
Age	0.03
Motivation for dismissal	0.02

Number of conditional convictions, *Number of particularly serious crimes*, *Age at the time of the first conviction* (to the actual degree of punishment), *Availability of early dismissals*, *Age at the time of the first conviction* (conditional or actual sentence), *Sex* are highlighted as the most important predictors.

The classification method in scoring modeling is most often used to predict risks. The use of several different instruments to *predict* inmates' propensity to commit future criminal recidivism provided the opportunity to reveal latent relationships and confirm previous findings. The following Data Mining tools were used for applied research (Fig. 3):

1. The initial data array was divided into two subsets using the method of Split Input Data into Training and Testing Samples (Classification). 34% of cases were used for testing the model and 66% for its construction.

2. Extraction of an equal number of cases prone to repeat criminal offenses and non-prone prisoners was carried out by the method of Stratified Random Sampling.

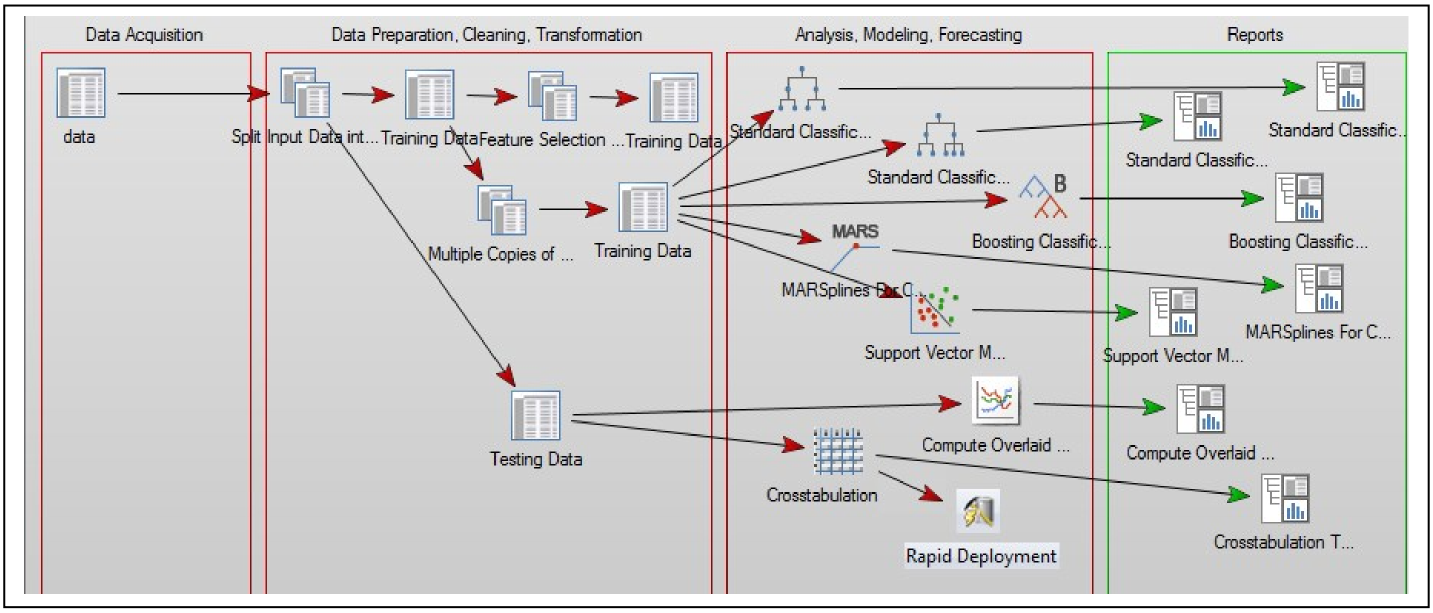

Fig. 3. Data Mining project window

3. The Feature Selection method was used to find the most significant independent variables for classifying prisoners into those prone to and those not prone to repeated criminal offenses.

4. Several predictive models of Machine Learning (ML) algorithms were used to identify and explain the correlation between the independent variables and the dependent variable. The Multiple Copies of Data Source procedure was previously performed, which made it possible to apply different algorithms to duplicates of the same data.

5. In order to determine the optimal of the constructed predictive models, the next tools were used to compare models: Lift Charts, Gain Charts, Cross tabulation. These indicators measure the benefits of using the model.

$$Lift = \frac{CNPOML}{CNPOMR},$$

where – CNPOML cumulative number of positive observations up to decile i using ML model; CNPOR – cumulative number of positive observations up to decile i using a random model:

$$Lift = \frac{CNPO}{TNPO},$$

where CNPO – Cumulative number of positive observations up to decile I; TNPO – total number of positive observations in the data.

6. In order to assess the accuracy of the prediction, the "hold-out" sample model and cross-validation (CV) were used - a procedure for empirical evaluation of the general ability of algorithms that are trained on precedents.

The Decision Tree method (CHAID) was used to classify prisoners into those prone to and those not prone to repeated criminal offenses and to predict the risks of committing them (Fig. 4).

As a result of applying the CHAID algorithm, 15 if-then conditions were fulfilled in relation to predicting the propensity of each of the prisoners to commit repeated criminal offenses in the future (prone/non-prone).

The constructed Decision Tree contains 15 terminal vertices. These are the vertices in which further classification of observations into prone and non-prone to criminal recidivism will not increase the accuracy of the predictive solution. The training sample was formed using the Stratified Random Sampling tool. These are 497 observations of inmates equally inclined and not inclined to repeat criminal offenses.

At the first stage of tree construction, the upper (root) vertex is divided into a terminal (left) vertex and a right vertex, which contains 495 cases, and is divided on the basis of the independent variable *Age at the time of the first conviction* into two more vertices, respectively 42 and 453 observations.

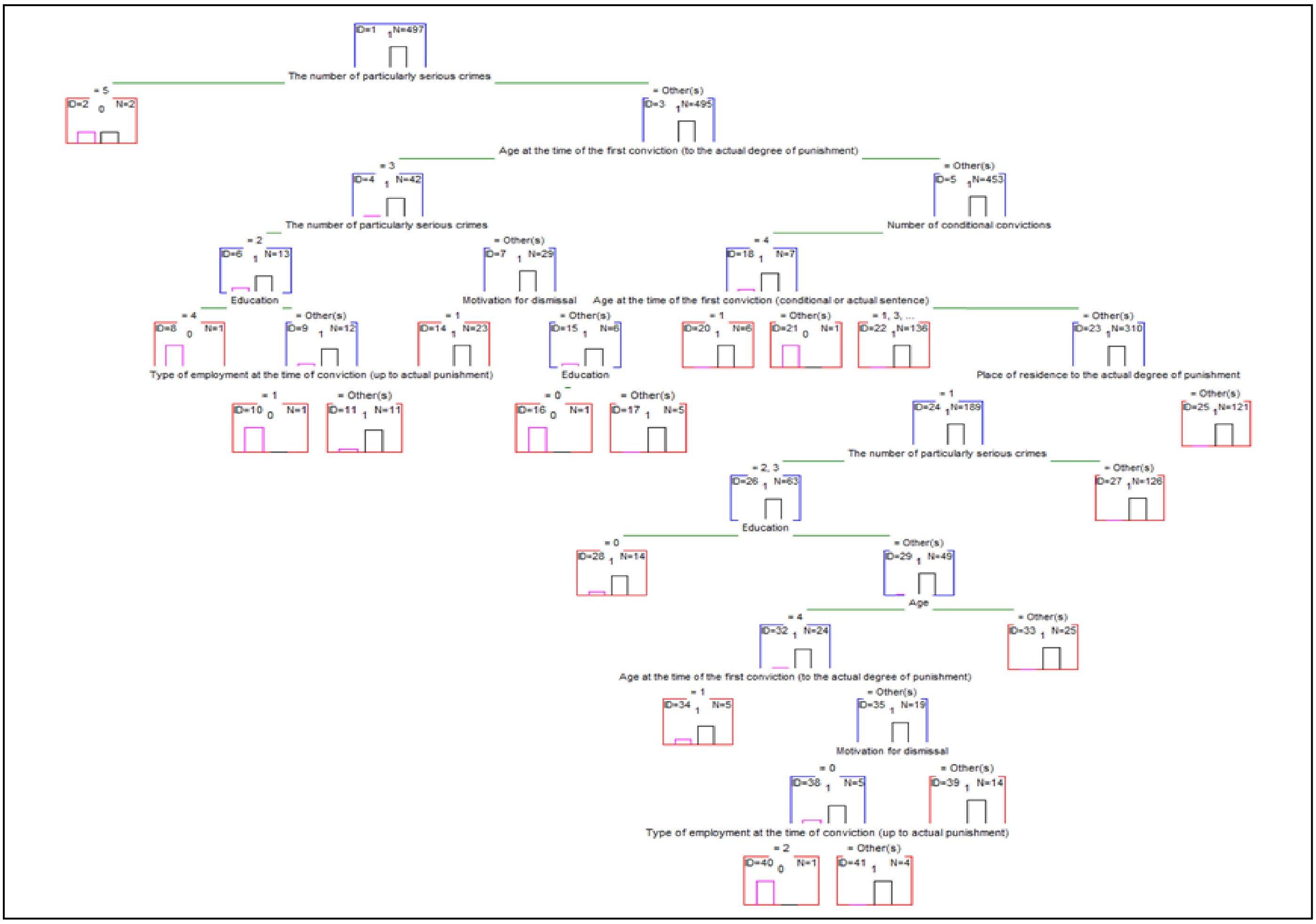

Fig. 4. The Decision Tree

The right one is divided on the basis of the independent variable *Number of conditional convictions* into two vertices with 7 and 446 observations, respectively. The left one is divided on the basis of the independent variable *Age at the time of the first conviction (conditional or actual sentence)* into two terminal vertices.

Most of the cases in these peaks are classified as prone to criminal recidivism. Decision rules can be obtained by moving along the path to each terminal vertex.

The classification matrix (CHAID model) compares the classifications that actually occur with the predicted classifications (those that are the majority at the corresponding terminal node) in order to summarize the classification accuracy for different input values. The matrix of actual and predicted frequencies of the initial values for the test set is displayed in the table (Table III).

TABLE III
MATRIX OF PREDICTED AND OBSERVED FREQUENCIES OF OUTPUT VALUES FOR THE TEST SET

	Observed 0	Observed 1
Predicted 0	8	3
Predicted 1	6	488

The Based Line Model is used as a measure of evaluating the usefulness of classification models. The Gains Chart) demonstrates the superiority of predictive models compared to the basic statistical model (Based Line Model), that is, the percentage of a given response in the main sample. The vertical axis shows the ratio of correctly predicted responses to the number of responses in the base model for a given percentile (the ratio of the boosting or lift value associated with the use of a particular model). For example, the Based Line Model on 20% of the data correctly predicts only 50% of the time, while the Boost Tree Model prediction accuracy on the same 20% of the data is twice as high. In general, the optimal model gives a 10-35% more accurate prediction, depending on the % of initial data, than the Based Line Model.

The classification matrix contains information about the number of correctly classified cases (the main diagonal of the matrix) and the number of incorrectly classified cases. The final model constructed can correctly predict the propensity of convicts to commit criminal recidivism in the future with 98% accuracy (488+8)/(488+8+3+6). The share of correctly predicted cases classified as not prone to criminal recidivism is 98%. The main goal of building a qualitative Scoring Model is to reduce the share of incorrectly classified negative cases (minimizing the number of cases not prone to criminal recidivism, predicted as prone). In the built model, this goal has been achieved. This is an extremely important nuance, - since the use of this model can help reduce the number of unjust sentences.

Comparative assessment of models

It is more efficient to experiment with different methods in the data mining or modeling process than to rely on one of these methods. Various tools will help to understand the problem in general or verify previous conclusions.

The Gain chart provides visualization of the resulting useful information obtained by one or more statistical models. The amplification map clearly demonstrates the gain in predicting using statistical models compared to using only basic statistical information (only the number of outputs in a normal sample).

The Gains chart (Fig. 5) is built for multiple predictive models based on training models using the Compute Overlaid Lift Charts procedure

Intelligent methods have been successfully applied to test data. In the future, they can be used to predict new cases of recidivism by criminals in the future.

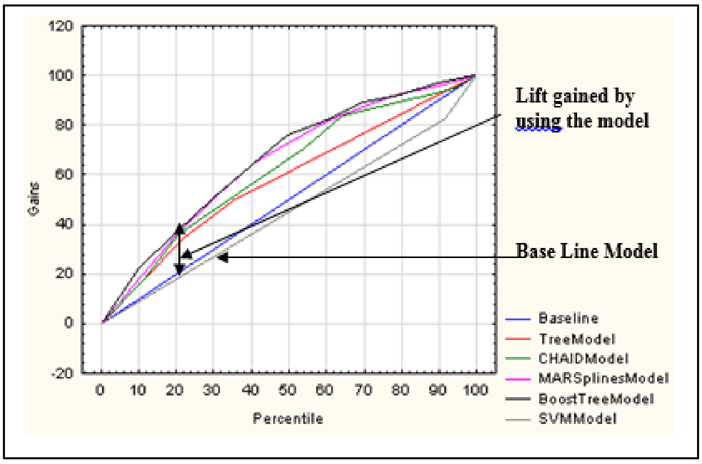

Fig. 5. Gains Chart for Recidivism = 0

CONCLUSION

We have discussed some aspects of the development of information and analytical support for the information security of Ukraine, namely internal security. Considering the complexity of the investigated problem, empirical studies were conducted using several different methods for the same real statistical data. In the field of information security, it is risky to rely on one of the modeling methods, therefore, for a more accurate understanding of the problem and verification of the obtained results, various modeling tools were applied.

The constructed cluster model for creating criminal profiles of criminals does not provide general patterns or motives for criminal recidivism, but it simplifies the understanding of criminal behavior and the correlation between the details of the criminal profile and provides support for decision-making in criminal justice, for example, in detecting fraudulent actions, predicting the probability recidivism, reducing bias when making pre-trial or court decisions, taking measures to prevent criminal offenses. To confirm the obtained results, an intellectual scoring model was built to determine the most significant factors that affect the propensity of prisoners to commit relapses. This model can also be used to assess and reduce wrongful convictions. Such predictive models can be used as an effective tool that provides assistance to law enforcement agencies in making pre-trial or judicial decisions and conducting crime prevention. An important advantage of the built models is their applied nature: they are developed on the basis of real statistical and dynamic data of prisoners serving their sentences in the penitentiary institutions of Ukraine. The obtained modeling results can provide important up-to-date information for making managerial decisions in the field of justice, in particular when making pre-trial or court decisions and conducting crime prevention, and become one of the important elements of information and analytical support of the justice bodies of Ukraine and information security of the state.

The next step of our research will be the creation of a discriminant model for clarifying the classification results obtained by the cluster analysis method, modeling the interdependencies between certain individual characteristics of prisoners, classifying new convicts based on the identified interdependencies and predicting their behavior regarding the possible commission of criminal offenses in the future. Such a model will be able to provide relevant information for developing an optimal strategy for investigating criminal cases and supporting decision-making regarding the internal security of the state.

REFERENCES

[1] "World Prison Brief," Institute for Crime & Justice Policy Research, 2021. Retrieved from https://www.prisonstudies.org

[2] World Population Review, "Incarceration Rates by Country," 2022. Retrieved from https://worldpopulationreview.com.

[3] F. Itulua-Abumere, "Criminal Profiling," London: Roehampton University, 2012. Retrieved from https://www.researchgate.net

[4] V. Tretynyk, and A. Chernyavskyj, "Creating a psychological portrait of a criminal offender based on methods of fuzzy logic," 2018. Retrieved from http://pmk.fpm.kpi.ua . [in Ukrainian].

[5] K. Berezka, O. Kovalchuk, S. Banakh, S. Zlyvko, and R. Hrechaniuk, "A Binary Logistic Regression Model for Support Decision Making in Criminal Justice," Folia Oeconomica Stetinensia, vol. 22(1), pp. 1-17, 2022. https://doi.org/10.2478/foli-2022-0001

[6] A. Babuta, M. Oswald, and C. Rinik, "Machine Learning Algorithms and Police Decision-Making," University of Winchester, 2018.

[7] M. Ghasemi, D. Anvari, M. Atapour. J. S. Wormith K. C. Stockdale, and R. J. Spiteri, "The Application of Machine Learning to a General Risk–Need Assessment Instrument," Prediction of Criminal Recidivism. Criminal Justice and Behavior, vol. 48, Issue 4, pp. 518-538, 2022. https://doi.org/10.1177/0093854820969753

[8] Yu. Rongqin, N. Långström, M. Forsman, A. Sjölander S Fazel., and Ya. Molero, "Associations between prisons and recidivism: A nationwide longitudinal study," National Center for Biotechnology Information, 2022. https://www.ncbi.nlm.nih.gov

[9] F.J.C.E. van Ginneken, and P. Nieuwbeerta, "Climate consensus: A multilevel study testing assumptions about prison climate," Journal of Criminal Justice, vol. 69, 2020. https://doi.org/10.1016/j.jcrimjus.2020.101693

[10] O. Kovalchuk, S. Banakh, M. Masonkova, V. Burdin, O. Zaverukha, and R. Ivanytskyy, "A Scoring Model for Support Decision Making in Criminal Justice", in Proc. 12th International Conference "Advanced Computer Information Technologies," pp. 116-120, 2022. https://doi.org/10.1109/ACIT54803.2022.9913182

[11] R. Berks, "Machine Learning Risk Assessments in Criminal Justice Settings," Springer; 1st ed., 2019.

[12] J. Chirakijja, "The Local Economic Impacts of Prisons," Department of Econometrics and Business Statistics Monash University, 2018. Retrieved from https://economics.smu.edu.sg

[13] A. Grawert, and T.-A. Craigie, "Mass. Incarceration Has Been a Driving Force of Economic Inequality," Brennar Center for Justice, 2020. Retrieved from https://www.brennancenter.org

[14] "Economics of Incarceration," Prison Policy Initiative, 2021. Retrieved from https://www.prisonpolicy.org

[15] M. McLaughlin, C. Pettus-Davis, D. Brown, D., C. Veeh, and T. Renn, "The Economic Burden of Incarceration in the United States," Institute for justice research and development, 2016. Retrieved from https://ijrd.csw.fsu.edu

[16] M. Mumford, D. Whitmore Schanzenbach, and R. Nunn, "The economics of private prison. REPORT," Brookings, 2020. https://www.brookings.edu.

[17] O. Kovalchuk, M. Shynkaryk, and M. Masonkova, (2021). "Econometric models for estimating the financial effect of cybercrimes," in Proc. 11th International Conference "Advanced Computer Information Technologies", pp. 381-384, 2021. https://doi.org/10.1109/ACIT52158.2021.9548490

[18] W. A. Petherick, and B. E. Turvey, "Criminal Profiling. In Criminal Profiling. An Introduction to Behavioral Evidence Analysis," Fourth Edition, pp. 1210-140, 2012. https://doi.org/10.1016/C2010-0-66252-3

[19] "Cluster Analysis'", Science Direct, 2015. Retrieved from https://www.sciencedirect.com

[20] F. Y. Jin, "Interpretable Machine Learning Credit Scoring Model," Asia Pacific University, 2019.