CLASSIFICATION OF DRUG CONSUMERS USING ARTIFICIAL INTELLIGENCE ALGORITHMS

KLASIFIKACIJA POTROŠAČA LIJEKOVA KORISTEĆI ALGORITME TEMELJENE NA UMJETNOJ INTELIGENCIJI

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ABSTRACT

Drug use disorder is one of the leading health problems in the world, which as a medical and social phenomenon has been attracting general attention for many years. Personal motives for which an individual decides to consume drugs vary. In this research dataset for drug users classification consists of information from 1885 respondents and their usage of 18 drugs, legal and illegal. Due to data imbalance, the research is based on three substances, ecstasy, cannabis, and nicotine. Three artificial intelligence algorithms, k-Nearest Neighbors (KNN), Support Vector Machine (SVM) and Multilayer Perceptron (MLP), were used to solve the classification problem. As a result, MLP achieved the highest AUC value compared to SVM and KNN.

Keywords: binary classification, k-Nearest Neighbors, Support Vector Machine, Multilayer Perceptron

SAŽETAK

Poremećaj zloupotrebe lijekova jedan je od vodećih zdravstvenih problema u svijetu koji kao medicinski fenomen već dugi niz godina privlači opću pozornost. Razlozi zloupotrebe lijekova razlikuju se od pojedinca do pojedinca. U ovom istraživanju skup podataka za klasifikaciju korisnika lijekova sastoji se od 1885 instanci od ukupnog broja ispitanika te njihove upotrebe legalnih i ilegalnih supstanci. Zbog nebalansiranosti podataka, istraživanje se temelji na tri supstance: ekstazi, kanabis i nikotin. Za rješavanje klasifikacijskog problema korištena su tri algoritma umjetne inteligencije: algoritam k-Najbližih susjeda (KNN), Metoda potpornih vektora (SVM) i Višeslojni perceptron (MLP). U usporedbi S KNN-om i SVM-om, MLP je rezultirao s najvećom AUC vrijednosti.

Ključne riječi: binarna klasifikacija, k-Najbližih susjeda, Metoda potpornih vektora, Višeslojni perceptron

INTRODUCTION

Addiction develops in a complex and hazy manner, and the potential for addictive behaviour varies between drugs. It is affected by the properties of the psychoactive substance, genetic susceptibility, personality and socio-economic group, and cultural and social environment [1]. The psychological characteristics of the user and the availability of the substance determine the choice of a psychoactive substance and, at least initially, the method and frequency of application. Fehrman et al. (2019) in their study describe a dataset with information on 1885 respondents and their usage of 18 drugs [2]. Participants were asked about various drugs, which were classified as either central nervous system depressants, hallucinogens or stimulants. The question is whether, based on certain information about the subject, his addiction to a particular drug can be predicted? For these reasons, the use of artificial intelligence (AI) in the classification of drug use is imposed. Algorithms used in this research are k-Nearest Neighbors (KNN), Supporting Vector Machine (SVM) and Multilayer Perceptron (MLP). Furthermore, these algorithms have been proven successful in various fields such as medicine [3 - 6], energy systems [7], maritime [8 - 9] and economy [10].
Yasnitskiy et al. (2015) demonstrate a computer program designed to determine a degree of the predisposition of a human to drug addiction based on the level of education, having friends who use drugs, temperament type, number of children in the family and financial situation [11]. Valero et al. (2014) show results using decision tree methods for exploring different personality profiles in drug consumers [12].
The aim of this research is to implement three different algorithms such as KNN, SVM and MLP for drug consumer classification. From the foregoing, the following hypotheses can be drawn:

- to achieve the highest possible accuracy and Area Under the ROC Curve (AUC), and
- to investigate the influence of different kernel functions (SVM) and the number of nearest neighbors (KNN) and optimization algorithms (ANN) on accuracy and AUC value.

MATERIALS AND METHODS

This section is divided into Dataset Description and Methods Description. The dataset description gives a short description of the parameters for drug consumers. Firstly, it is necessary to describe the given dataset and the concept of approaching to the classification problem. Afterwards, the description of AI algorithms and performance measures is given.

DATASET DESCRIPTION

Dataset consists of 32 parameters collected for 1885 participants [2]. The data is divided into two groups, input and output variables. Input variables refer to: age, gender, education, ethnicity, Nscore, Escore, Oscore, Ascore, Cscore, Impulsivity and SS. Personal measures refer to five personal factors, i.e. [2]:

- Nscore (neuroticism): long-term tendency to experience negative emotions such as nervousness, tension, anxiety and depression,
- Escore (extraversion): manifested by open, warm, active, talkative and cheerful characteristics,
- Oscore (openness to experience): general propensity for art, unusual ideas and imaginative, creative, unconventional and broad interests,
- Ascore: the dimension of interpersonal relationships characterized by trust, modesty, kindness, compassion and cooperation, and
- Cscore (conscientiousness): tendency to organize, reliability and perseverance.

Impulsivity is measured in relation to behaviors and contains three categories: motor (without thinking), intentional and unplanned impulsivity (regardless of consequences). Output variables relate to the consumption of the following substances: alcohol, amphetamines, amyl, benzos, caffeine, cannabis, chocolate, cocaine, crack, ecstasy, heroin, ketamine, legal lifters, methadone, fungi, nicotine, semester (fictitious drug), VSA (abuse of volatile substances). Since data range of output variables is fairly large, the research focuses on the following substances: cannabis, nicotine and ecstasy. Since the dataset is unbalanced, three aforementioned substances were selected because they tend to have relatively balanced data. Based on this data the goal is to prove that artificial intelligence algorithms can achieve satisfactory results despite the small amount of data. For each substance 80% (1508 data-points, i.e. 1508 consumers) are used as a training set and 20% (377 data-points, i.e. 377 consumers) as a testing set. The group of non-users (0) consists of two categories: never consumed (CL0) and consumed more than a decade ago (CL1). The user group (1) consists of 5 categories: consumed during last decade (CL2), consumed during last year (CL3), consumed during last month (CL4), consumed during last week (CL5) and consumed yesterday (CL6).

Methods description

Artificial intelligence algorithms (MLP, SVM and KNN) and the performance measures used for the purpose of this research are briefly described below.

Multi-layer Perceptron

The multilayer perceptron (MLP) is a deep artificial neural network. MLP is composed of an input layer for receiving signals, an output layer that decides about the input, and between these two layers there is an arbitrary number of hidden layers [13]. Neural network parameters are: number of hidden layers, the maximum number of iterations, activation function, alpha, optimization algorithm and learning rate. In this research, MLP is trained using two different optimization algorithms these are:

- Stochastic Gradient Descent (SGD) and
- Adam.

Activation functions that can be applied to hidden and output layers are [14]:

Relu

(1) $$f(x) = \begin{Bmatrix} 0, & if\ x < 0 \\ x, & if\ x \geq 0 \end{Bmatrix},$$

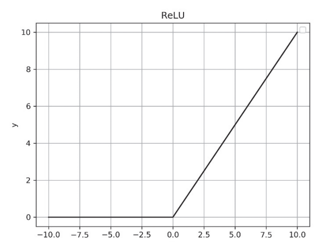

Fig.1. Activation function ReLU

Tanh

(2) $$f(x) = \tanh(x) = \frac{2}{1+e^{-2x}} - 1,$$

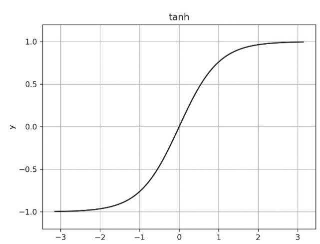

Fig. 2. Activation function tanh

Logistic

(3) $$f(x) = \frac{1}{1+e^{-x}},$$

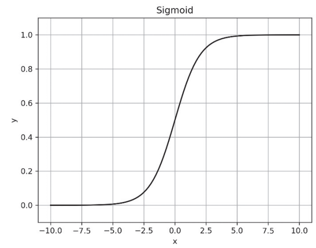

Fig. 3. Sigmoid activation function

Identity

(4) $$f(x) = cx.$$

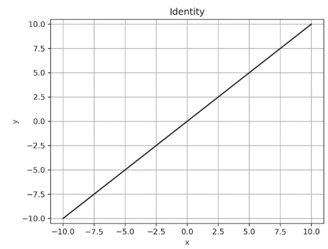

Fig. 4. Identity activation function

Support Vector Machine

The support vector machine (SVM) is a machine learning algorithm applied to a supervised learning problem (as well as MLP), i.e. a set of input-output pairs is trained. To begin with, it is necessary to display each data item as a point in n-dimensional space (where n represents the number of features from the dataset), with the value of each feature being the value of a certain coordinate [15]. It is then necessary to perform the classification by finding a hyper-plane that separates the two classes. Values along the hyper-plane represent limit values which are more difficult to classify into an actual value. During the classification, it is necessary to get acquainted with the parameters of the algorithm. The parameters of the SVM are: regularization parameter (C), kernel type, degree of polynomial function, and gamma coefficient. In this research, the following three different kernel functions are used [16]:

- Linear,
- Radial Basis Function (RBF) and
- 3rd degree Polynomial.

Table 1. Neural network parameters and architecture for ecstasy consumption

Sequence of changing neural network parameters	Number of neurons per layer	Maximal number of iterations	Activation function	Alpha	Solver	Learning rate
1.	100	100	tanh	0.05	adam	constant
2.	100	100	relu	0.0001	adam	constant
3.	50, 100, 50	100	identity	0.0001	adam	constant
4.	100	100	logistic	0.05	sgd	adaptive
5.	10	150	tanh	0.05	sgd	constant
6.	50, 100, 50	450	tanh	0.0001	adam	constant
7.	50,100, 50	500	relu	0.05	sgd	constant
8.	100	500	relu	0.05	adam	adaptive
9.	100	500	identity	0.05	adam	adaptive
10.	10, 20, 10	500	identity	0.0001	sgd	adaptive
11.	10	155	logistic	0.05	adam	adaptive
12.	50,100,50	100	logistic	0.05	adam	adaptive

Table 2. Neural network parameters and architecture for cannabis consumption

Sequence of changing neural network parameters	Number of neurons per layer	Maximal number of iterations	Activation function	Alpha	Solver	Learning rate
1.	100	100	tanh	0.05	adam	constant
2.	100	100	relu	0.0001	adam	constant
3.	50, 100, 50	100	identity	0.0001	adam	constant
4.	100	400	logistic	0.05	sgd	adaptive
5.	10	200	tanh	0.05	sgd	constant
6.	50, 100, 50	400	tanh	0.0001	adam	constant
7.	50,100, 50	400	relu	0.05	sgd	constant
8.	100	500	relu	0.05	adam	adaptive
9.	100	200	identity	0.05	adam	adaptive
10.	10, 20, 10	150	identity	0.0001	sgd	adaptive
11.	10	150	logistic	0.05	adam	adaptive
12.	50,100,50	40	logistic	0.05	adam	adaptive

K-Nearest Neighbor method

One of the commonly used machine learning algorithms is k-Nearest Neighbor. KNN is a model that classifies data points based on points that are most similar to it. When implementing the algorithm, the first step is to transform the data points into feature vectors [17]. The algorithm then finds the distances between the mathematical values of these points. The most common way to find the distance is by calculating the Euclidean distance shown by the Eq.5. This equation is referred to an n-dimensional Euclidean space [18].

$$d(p,q) = d(q,p) = \sqrt{(q_1 - p_1)^2 + (q_2 - p_2)^2 + \cdots + (q_n - p_n)^2} = \sqrt{\sum_{i=1}^{n} (q_i - p_i)^2}, \quad (5)$$

where:
q – represents a distance between points in relation to y axis,
p – represents a distance between points in relation to x axis.
KNN calculate the distance between each data point and the test data. It is then determined how likely it is that the points are similar to the test data and classified according to which points are most likely [19]. The most important parameter of the algorithm is k.

Performance Evaluation

Before the classification, it is necessary to describe certain metrics in order to analyze the obtained results more precisely. Two metrics relevant for this research are: accuracy and AUC (Area Under Curve-Receiver Operating Characteristics). Accuracy represents the ratio of the number of correct predictions and the total number of predictions. For binary classification, accuracy can be calculated by following equation [20]:

Table 3. Neural network parameters and architecture for nicotine consumption

Sequence of changing neural network parameters	Number of neurons per layer	Maximal number of iterations	Activation function	Alpha	Solver	Learning rate
1.	100	100	tanh	0.05	adam	constant
2.	100	100	relu	0.0001	adam	constant
3.	50, 100, 50	100	identity	0.0001	adam	constant
4.	100	100	logistic	0.05	sgd	adaptive
5.	10	130	tanh	0.05	sgd	constant
6.	50, 100, 50	400	tanh	0.0001	adam	constant
7.	50,100, 50	300	relu	0.05	sgd	constant
8.	100	300	relu	0.05	adam	adaptive
9.	100	200	identity	0.05	adam	adaptive
10.	10, 20, 10	100	identity	0.0001	sgd	adaptive
11.	10	200	logistic	0.05	adam	adaptive
12.	50,100,50	200	logistic	0.05	adam	adaptive

$$(6) \quad \text{Accuracy} = \frac{TP + TN}{TP + TN + FN + FP},$$

where:
TP- represents true positives,
TN - represents true negatives,
FP - represents false positives and
FN - represents false negatives.

ROC curve is a probability curve for different classes and shows how good the model is for distinguishing given classes in the context of predicted probability. The x-axis of the ROC curve represents false positive rates (FPR), while the y-axis represents true positive rates (TPR) [20]. AOC represents the area under the ROC curve.

RESULTS AND DISCUSSION

The three aforementioned AI algorithms are applied to each substance in order to achieve high-quality classification. The aim of the classification is to achieve the highest possible accuracy and AUC values. In other words, it is necessary for each substance to classify as precisely as possible the class of non-users (classified under 0) under non-users and the class of users (classified under 1) under the class of users. The parameters of each algorithm will strive to be best adjusted in order to achieve satisfactory results.

Multi-Layer Perceptron
Firstly, MLP method is implemented on data of ecstasy, cannabis and nicotine users.

Ecstasy
Several neural network parameters and architectures are tested in order to achieve optimal results. The neural network architectures for ecstasy consumption are shown in Table 1.

Accuracy and AUC values for different neural network architectures are shown in Fig.5.

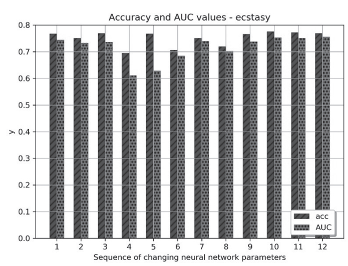

Fig. 5. Accuracy and AUC values for different neural network architectures for ecstasy consumption

The highest accuracy was achieved in the 10th neural network architecture. When comparing the 9th and 10th neural network architectures where the same activation functions are used, the following can be concluded: with a larger number of neurons per layer and a smaller number of maximum iterations with the sgd solver, higher accuracy is achieved. The lowest accuracy is obtained in 6th neural network architecture where a larger number of neurons per layer and iterations with adam solver along with tanh activation function is used. As for AUC, the highest value is achieved in the 12th neural network architecture. ROC curve obtained with best performing neural network architecture (12th) for ecstasy classification problem is shown in Fig. 6.

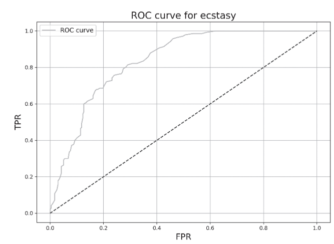

Fig. 6. ROC curves for ecstasy

Cannabis
Different neural network architectures for cannabis consumption are tested to achieve optimal results. Several neural network parameters and architectures are shown in Table 2.

Accuracy and AUC values for different neural network architectures for cannabis consumption are shown in Fig 7.

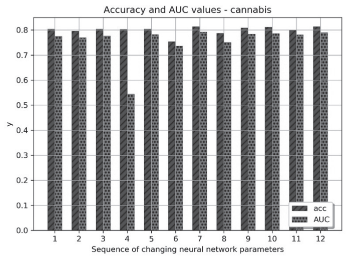

Fig. 7. Accuracy and AUC values for different neural network architectures for cannabis consumption

Despite different parameters, the highest accuracy is 0.82. The 12th and 7th neural network architecture represent the same result, but the 12th uses the logistic activation function and thus increasing the maximum iteration cannot reduce the value of the loss. Other accuracies do not deviate excessively. The 2nd, 6th, and 8th neural network architectures have the lowest accuracy. The reason for this is mostly the use of adam solver with a low number of iterations. By comparing 1st neural network architecture (high accuracy) and 6th (lowest accuracy) it can be seen that by using the tanh function it is advisable to reduce the number of maximum iterations and the number of hidden layers. In Figure 8. the ROC curve for cannabis is shown.

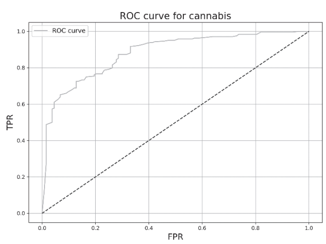

Fig. 8. ROC curves for cannabis

From Fig. 8. it can be concluded that the selected neural network parameters gave quite satisfactory results. The ROC curve deviates slightly from the ideal characteristic.

Nicotine

Several neural network parameters and architectures are tested in order to achieve optimal results. The different neural network architectures for nicotine consumption are shown in Table 3.

Accuracy and AUC values for different neural network architectures for nicotine consumption are shown in Fig. 9.

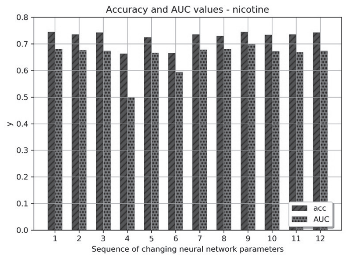

Fig. 9. Accuracy and AUC values for different neural network architectures for nicotine consumption

The highest accuracy is achieved in the 1st and 9th neural network architecture. These architectures use a low number of maximum iterations, 100 neurons per layer, and adam as solver. Comparing the 1st architecture with the 6th neural network architecture, it can be concluded that increasing the number of neurons per layer and the number of maximum iterations significantly reduces the accuracy. Such a comparison is excellent because with similar parameters, higher accuracy (case 1) or lower accuracy (case 6) can be obtained. As for AUC, the highest value is achieved in 9th neural network architecture. Figure 10. represents the ROC curve for nicotine.

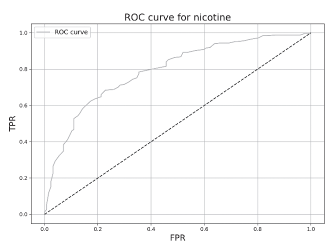

Fig. 10. ROC curves for nicotine

SVM

SVM method is implemented on all aforementioned substances (ecstasy, cannabis and nicotine). Regularization parameter (C) is 1.

Ecstasy

The SVM algorithm is applied to the ecstasy dataset. Obtained results for different kernels are shown in Figure 11.

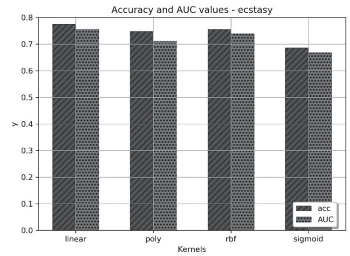

Fig. 11. Accuracy and AUC values for different kernels for ecstasy consumption

It can be concluded that the highest accuracy value was achieved by implementing a linear kernel. AUC values are also quite accurate as they follow accuracy value. ROC curve obtained with best performing kernel (linear) for ecstasy classification problem is shown in Fig. 12.

Cannabis

The SVM algorithm is also applied to the cannabis dataset. Results with different kernels are shown in Figure 13.

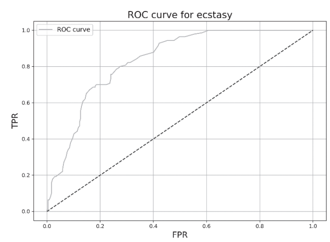

Fig. 12. ROC curves for ecstasy

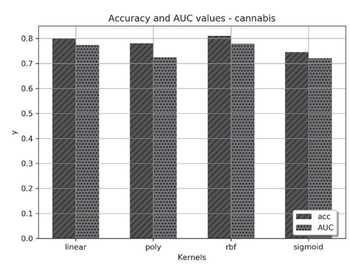

Fig. 13. Accuracy and AUC values for different kernels for cannabis consumption

It can be concluded that the accuracy of a particular kernel does not differ excessively. But as it can be noticed, the highest accuracy was achieved by implementing a rbf kernel. As for AUC values, they do not deviate from the accuracy value and follow the selection of the most adequate kernel. From

Figure 14. it can be concluded that the selected kernels gave quite satisfactory results. Therefore, the obtained ROC curve does not deviate much from the ideal characteristic.

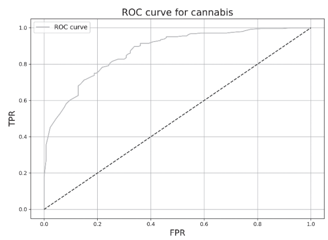

Fig. 14. ROC curves for cannabis

Nicotine

Finally, the SVM algorithm is applied to the nicotine dataset. Different kernels for nicotine consumption are shown in Figure 15.

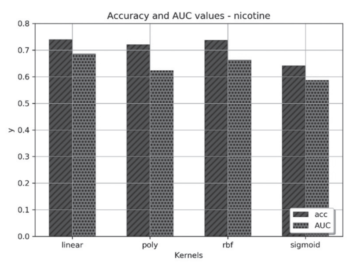

Fig. 15. Accuracy and AUC values for different kernels for nicotine consumption

From Fig. 15. it can be noticed; the highest accuracy was achieved by implementing a linear kernel. As for AUC values, they do not deviate from the accuracy value and they follow the selection of the most adequate kernel. The highest AUC value was achieved also with implementing a linear kernel. Figure 16. shows the ROC curve for nicotine.

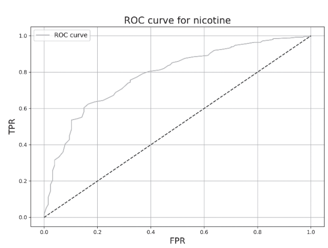

Fig. 16. ROC curves for nicotine

KNN

Lastly, KNN method is implemented on ecstasy, cannabis, and nicotine substance.

Ecstasy

With regard to ecstasy consumption data, consumer classification will be performed using the k-NN algorithm. When choosing the optimal number of neighbors, it is necessary to calculate the error rate of the value k in a certain (arbitrary) range, as shown in Figure 17.

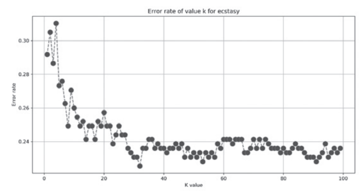

Fig. 17. Error rate of the value k for ecstasy

The highest accuracy of the algorithm is expected in the range of the number of neighbors from 29 to 34. Accuracy and AUC values for a different number of neighbors for ecstasy consumption are shown in Fig 18.

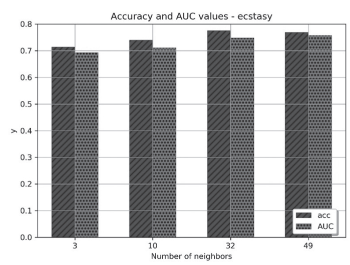

Fig.18. Accuracy and AUC values for different number of neighbors for ecstasy consumption

The highest accuracy was obtained by implementing the number of neighbors 32, while the highest AUC value was obtained by implementing the number of neighbors 49. The difference between these two metrics is not as much dissimilar so it can be concluded that the adequate number of neighbors for ecstasy consumption is 49. Figure 19. shows the ROC curve for ecstasy (for number of neighbors 49).

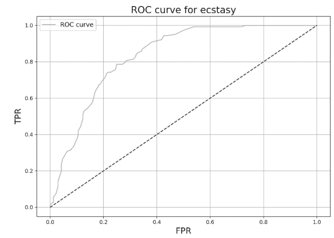

Fig. 19. ROC curves for cannabis

Cannabis

Regarding cannabis consumption data, consumer classification is performed using the k-NN algorithm. Error rate of the value of k in a certain (arbitrary) range is shown in Figure 20.

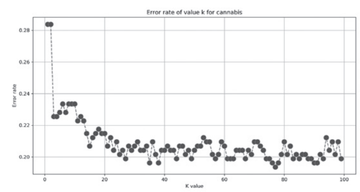

Fig. 20. Error rate of the value k for cannabis

The highest accuracy of the algorithm is expected in the range of the number of neighbors from 75 to 77. Accuracy and AUC values for a different number of neighbors for cannabis consumption are shown in Fig 21.

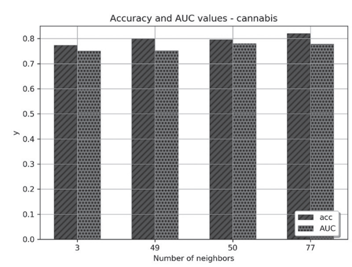

Fig. 21. Accuracy and AUC values for different number of neighbors for cannabis consumption

The highest accuracy was obtained by utilizing the number of neighbors 77, while the highest AUC value was obtained by utilizing the number of neighbors 50. In this case, as with ecstasy users, the difference in obtained values is not as much dissimilar so it can be concluded that the adequate number of neighbors for cannabis consumption is 50. Figure 22. shows the ROC curve for cannabis (for number of neighbors 50).

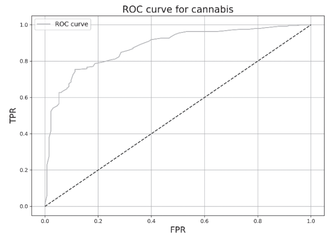

Fig. 22. ROC curves for cannabis

Nicotine
k-NN method is implemented on data of nicotine users. The error rate of the value k in a certain (arbitrary) range is shown in Figure 23.

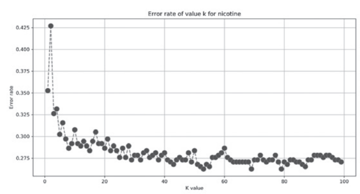

Fig. 23. Error rate of the value k for nicotine

The highest accuracy of the algorithm is expected in the range of the number of neighbors from 50 to 100. Accuracy and AUC values for a different number of neighbors for nicotine consumption are shown in Figure 24.

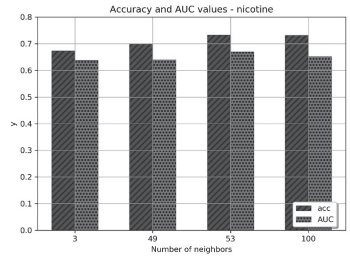

Fig. 24. Accuracy and AUC values for different number of neighbors for nicotine consumption

The highest accuracy was obtained by utilizing the number of neighbors 53, while the highest AUC value was obtained by implementing the number of neighbors 100. Figure 25. shows the ROC curve for cannabis users. It can be seen that the selected parameters gave quite satisfactory results. When compared with other substances, the results for nicotine are not as promising, especially those which can be seen from obtained AUC values.

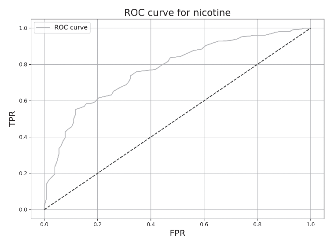

Fig. 25. ROC curves for nicotine

Fehrman et al. (2017) demonstrate the results for classification tasks, sensitivity and specificity were greater than 70% while in the case of cannabis is 75% [22]. In our research the greatest values of accuracy and AUC were greater than 80%.

CONCLUSION

Elaine Fehrman collected drug consumption data in the period from March 2011 to March 2012. The usable sample consisted of 1885 participants. Data for three substances: ecstasy, cannabis and nicotine used in this research proved to be relatively balanced in comparison to other substances. The aim was to examine whether AI algorithms can classify drug users with satisfactory results based on a small amount of data. For ecstasy, it can be concluded that the classification problem was best solved by implementing the SVM algorithm. The accuracy reaches the highest value, while the ROC curves do not differ excessively. In the case of cannabis, the results are equally effective, but the MLP algorithm can be highlighted in order to obtain the highest accuracy. Equal conclusions can also be drawn for the nicotine. The accuracies are about the same, while the ROC curves do not differ excessively.
In general, the highest AUC value achieved was for drug consumers of cannabis by utilizing MLP. Furthermore, the highest achieved AUC values for ecstasy and nicotine drug users are also quite acceptable. Implemented algorithms showed promising results but with more data, these algorithms have real potential to be implemented on other relevant drugs presented in the dataset. However, with the existing dataset, implemented algorithms can only be used with chosen substances.

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REFERENCES

1. Kutlu MG, Gould TJ. Effects of drugs of abuse on hippocampal plasticity and hippocampus-dependent learning and memory: contributions to development and maintenance of addiction. Learn.Mem., 2016 Oct 1;23(10):515-33.
2. Fehrman E, Egan V, Gorban AN, Levesley J, Mirkes EM, Muhammad AK. Drug Use and Personality Profiles. InPersonality Traits and Drug Consumption 2019 (pp. 5-33). Springer, Cham.
3. Lorencin I, Anđelić N, Šegota SB, Musulin J, Štifanić D, Mrzljak V, et al. Edge detector-based hybrid artificial neural network models for urinary bladder cancer diagnosis. InEnabling AI Applications in Data Science 2021 (pp. 225-245). Springer, Cham.

4. Musulin J, Smolčić K, Štifanić D, Španjol J, Car Z. Bladder cancer detection: Integration of feature extraction algorithms and MLP. 5th International Workshop on Data Science, 2020.
5. Car Z, Baressi Šegota S, Anđelić N, Lorencin I, Mrzljak V. Modeling the Spread of COVID-19 Infection Using a Multilayer Perceptron. Computational and Mathematical Methods in Medicine. 2020 May 29;2020.
6. Musulin J, Štifanić D, Zulijani A, Ćabov T, Dekanić A, Car Z. An Enhanced Histopathology Analysis: An AI-Based System for Multiclass Grading of Oral Squamous Cell Carcinoma and Segmenting of Epithelial and Stromal Tissue. Cancers. 2021 Jan;13(8):1784.
7. Elsheikh AH, Sharshir SW, Abd Elaziz M, Kabeel AE, Guilan W, Haiou Z. Modeling of solar energy systems using artificial neural network: A comprehensive review. Solar Energy. 2019 Mar 1;180:622-39.
8. Štifanić D, Musulin J, Car Z, Čep R. Use of Convolutional Neural Network for Fish Species Classification. Pomorski zbornik. 2020 Dec 30;59(1):131-42.
9. Baressi Šegota S, Lorencin I, Musulin J, Štifanić D, Car Z. Frigate Speed Estimation Using CODLAG Propulsion System Parameters and Multilayer Perceptron. NAŠE MORE: znanstveni časopis za more i pomorstvo. 2020 May 18;67(2):117-25.
10. Štifanić D, Musulin J, Miočević A, Baressi Šegota S, Šubić R, Car Z. Impact of COVID-19 on Forecasting Stock Prices: An Integration of Stationary Wavelet Transform and Bidirectional Long Short-Term Memory. Complexity. 2020 Jan 1;2020.
11. Yasnitskiy LN, Gratsilev VI, Kulyashova JS, Cherepanov FM. POSSIBILITIES OF ARTIFICIAL INTELLECT IN DETECTION OF PREDISPOSITION TO DRUG ADDICTION. Perm University Herald. Series Philosophy. Psychology. Sociology/Vestnik Permskogo Universiteta. Filosofia, Psihologia, Sociologia. 2015 Jan 1(1).
12. Valero S, Daigre C, Rodríguez-Cintas L, Barral C, Gomà-i-Freixanet M, Ferrer M, et al. Neuroticism and impulsivity: their hierarchical organization in the personality characterization of drug-dependent patients from a decision tree learning perspective. Comprehensive psychiatry. 2014 Jul 1;55(5):1227-33.
13. Abdar M, Yen NY, Hung JC. Improving the diagnosis of liver disease using multilayer perceptron neural network and boosted decision trees. JMBE, 2018 Dec 1;38(6):953-65.
14. Lai Z, Deng H. Medical Image Classification Based on Deep Features Extracted by Deep Model and Statistic Feature Fusion with Multilayer Perceptron‬ . Computational intelligence and neuroscience. 2018 Sep 12;2018.
15. Huang Y, Zhao L. Review on landslide susceptibility mapping using support vector machines. Catena. 2018 Jun 1;165:520-9.
16. Musulin J, Štifanić D, Lorencin I, Baressi Šegota S, Anđelić N, Borović E, et al. COMPARISON OF THREE ARTIFICIAL INTELLIGENCE ALGORITHMS FOR SEPSIS PREDICTION, WOH, 2020.
17. Zhang S, Li X, Zong M, Zhu X, Wang R. Efficient knn classification with different numbers of nearest neighbors. IEEE transactions on neural networks and learning systems. 2017 Apr 12;29(5):1774-85.
18. Lubis AR, Lubis M. Optimization of distance formula in K-Nearest Neighbor method. Bulletin of Electrical Engineering and Informatics. 2020 Feb 1;9(1):326-38.
19. Fan GF, Guo YH, Zheng JM, Hong WC. Application of the weighted k-nearest neighbor algorithm for short-term load forecasting. Energies. 2019 Jan;12(5):916.
20. Gunawardana A, Shani G. A survey of accuracy evaluation metrics of recommendation tasks. JMLR, 2009 Dec 1;10(12).
21. Kumar, Rajeev, and Abhaya Indrayan. "Receiver operating characteristic (ROC) curve for medical researchers." Indian pediatrics 48.4 (2011): 277-287.
22. Fehrman E, Muhammad AK, Mirkes EM, Egan V, Gorban AN. The five factor model of personality and evaluation of drug consumption risk. InData science 2017 (pp. 231-242). Springer, Cham.