Analyzing the Relationship between the Personality Traits and Drug Consumption (Month-based user Definition) using Rough Sets Theory

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***Abstract*—There is no doubt that the use of drugs has significant consequences for society, it introduces risk into the human life and causing earlier mortality and morbidity. Being a conscientious member of society, we must go ahead to prevent these young minds from life-threatening addiction. Owing to the computational complexity of wrapper approaches, the poor performance of filtering techniques, and the classifier dependency of embedded approaches, artificial intelligence and machine learning systems can provide useful tools for raising the prediction rate of drug users. Recently, the psychologists approved the recent personality traits Five Factor Model (FFM) for understanding human individual differences. The aim of this work is to propose a rough sets theory based method to investigate the relationship between drug user/non-user (month-based user definition) and the personality traits. The data of five factor personality profiles, impulsivity, sensation-seeking and biographical information of users of 21 different types of legal and illegal drugs are used to fetch all reducts and finally a set of classification rules are created to predict the drug user/non-user(month-based user definition). The outcomes demonstrate the novelty of the current work which can be summarized as The set of generalized classification rules which pronounced with logic functions build a knowledge base with excellent accuracy to analyze drug misuse successfully and may be worthy in many applications.**

***Keywords*—Classification; personality traits; five factor model; rules extraction; drug abuse detection; rough sets theory; feature selection**

I. Introduction

One of the extreme serious matters taking into account the mental health in these days is drug addiction, where it has the ability to devastate life and a nation readily for their toxic and addictive effects. Drug intemperance means" the picking of diverse drugs illegally and being addicted to those drugs". Drug intemperance has turned into a severe truth for which the young descents from all lifestyles are influenced silently. Dissatisfaction is the cause for this intemperance, unemployed matters, political outburst, non-attendance of homely relationships, and non-attendance of ardent love fellowship which offers rise to disappointments [1]. Drug is having been thought to be one of the extreme used psychoactive substances. as stated by world health organization, drug consuming leads to the death of three million as well as 5.1% of several universal diseases all over the world yearly [2]. The practical importance of the issue of estimating individual's risk of intemperance drugs is very high [3]. The connection of personality traits to risk of intemperance drugs is a continuous problem [4]. Many studies had been done to find the answer of the following Questions -"How do personality, gender, education, nationality, age, and other attributes affect this risk? Is this dependence different for different drugs? Which personality traits are the most important for evaluation of the risk of consumption of a particular drug, and are these traits different for different drugs? Is the prediction of drugs usage by a person helpful to prevent the persons from getting addicted to drugs?" Also, some related works had been done by researchers on drugs and addiction predictions to improve the methods which are used. Bergh [5] proposed a way to Predicting Alcohol Consumption in Adolescents from Historical Text Messaging Data. Belcher et al. [6] studied the personality traits and sensitivity or resilience to drug intemperance. Weissman, et al. [7] studied the effects of the drug intemperance adolescent and it is found that there is a strong connection between reward and cognitive control brain networks. Andreassen et al. [8] studied the relevance between behavioral addictions and the FFM of personality. Kumar, et. al. [9] proposed efficient prediction of drug–drug interaction using deep learning models. In this work all the questions which posed above have been reformulated as classification problem and an effective data mining technique dependent on rough set theory was employed to address these issues and extracting classification rules to predict the Drug User/Non-User (month-based user definition).

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II. Research Problem

Psychologists tried many times to identify the connections between personality traits and drug user/non-user. Many studies are done and data mining techniques and methodologies had been used to manage these issues such as decision trees, linear discriminant analysis, and statistics estimation techniques [10]. The main aim of this work is to find answers to these questions: Which personality traits have the great importance for estimation of the risk of abusing drugs, and are these traits different for different drugs? What are the effects of personality, gender, education, nationality, age, and other factors on abusing drugs? What about this dependence for several drugs?

A. Personality Traits

In recent years and due to the development in scientific research, the psychologists approved the recent personality traits Five Factor Model (FFM) for realization of human individual variances [11]. It consists of Neuroticism (N), Extraversion (E), Openness to Experience (O), Agreeableness (A), and Conscientiousness (C). These traits can be defined as follow:

- N : "Neuroticism is a long-term tendency to experience negative emotions such as nervousness, tension, anxiety and depression (associated adjectives [10]: anxious, self-pitying, tense, touchy, unstable, and worrying)”
- E: " Extraversion manifested in characters who are outgoing, warm, active, assertive, talkative, and cheerful; these persons are often in search of stimulation (associated adjectives: active, assertive, energetic, enthusiastic, outgoing, and talkative)”.
- O: "Openness to experience is associated with a general appreciation for art, unusual ideas, and imaginative, creative, unconventional, and wide interests (associated adjectives: artistic, curious, imaginative, insightful, original, and wide interest)”.
- A: "Agreeableness is a dimension of interpersonal relations, characterized by altruism, trust, modesty, kindness, compassion and cooperativeness (associated adjectives: appreciative, forgiving, generous, kind, sympathetic, and trusting)”.
- C: "Conscientiousness is a tendency to be organized and dependable, strong-willed, persistent, reliable, and efficient (associated adjectives: efficient, organised, reliable, responsible, and thorough)".

The values of the five factors (N, E, O, A, C) are utilized as inputs in various statistical methodologies for prediction, diagnosis, and risk estimation. These methodologies and techniques are used a wide range of fields where personality has a great importance such as medicine, psychology, psychiatry, education, sociology, and many others areas. Other two additional feature of personality confirmed to be leading for analysis of matter use, Impulsivity (Imp) and Sensation-Seeking (SS) [12].

- Imp: "Impulsivity is defined as a tendency to act without adequate forethought "
- SS: "Sensation-Seeking is defined by the search for experiences and feelings, that are varied, novel, complex and intense, and by the readiness to take risks for the sake of such experiences"

B. Rough Sets Theory

Rough sets theories (RST) is the core of most recent approximations based mathematical model to investigate the imprecision and uncertainty present in knowledge [13-17], as well as extract decision rules which act as classification scheme for prediction. We can say that it is a tool for data mining or knowledge discovery in relational databases. It is a formal approximation of a crisp set defined by its two approximations namely, Upper and Lower approximation [18] as shown in Fig. 1.

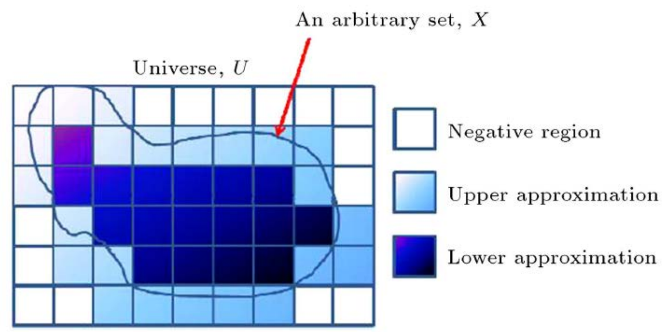

Fig. 1. Represen Tation of a Set Approximation of an Arbitrarily Set X in U.

The definition of the indiscernible relation IND(B) is:

$$IND(B) = \{ (x, y) \in U \mid \forall a \in B, a(x) = a(y) \} \tag{1}$$

Also, in decision system (U, A) let $B \subseteq A$ and $X \subseteq U$, the lower approximate $\underline{B}(x)$, upper approximate $\overline{R}(x)$ and the boundary of X denoted by BND(X) are written as:

$$\underline{B}(x) = \{ x \in U \mid [x]_B \subseteq X \} \tag{2}$$

$$\overline{B}(x) = \{ x \in U \mid [x]_B \cap X \neq \varnothing \} \tag{3}$$

$$BND(X) = \overline{B}(x) - \underline{B}(x) \tag{4}$$

The B-positive region of X and The B-negative region of X, denoted as $POS_B(X)$, $NEG_B(X)$ respectively are written as:

$$POS_B(X) = \underline{BX} \tag{5}$$

$$NEG_B(X) = U - \underline{BX} \tag{6}$$

The accuracy of approximation can be written as:

$$\alpha_B(X) = \frac{|\underline{BX}|}{|\overline{BX}|} \tag{7}$$

Where $|x|$ is the cardinality of X. Obviously $0 \leq \alpha_B(X) \leq 1$. The rough membership function can be written as

$$\mu_X^B(x) = \frac{|X \cap [x_i]_{Ind(B)}|}{|[x_i]_{Ind(B)}|} \tag{8}$$

Obviously,

$$\mu_X^B(x) \in [0,1] \tag{9}$$

III. Analysis

In the life of the any human there are various factors (attributes) for addiction that lead to increase the probability of drug consumption. Some of these attributes correlated with psychological, social, environmental, and economic characteristics [19, 20]. The most important risk factors are likewise associated with personality traits [21]. So this study proposes a methodology based on rough set theory to extract decision rules for predicting drug user/non-user (month-based user definition). We defined different categories (classifications) of “drug users” based on the regency of use as follows: class of "non-users", "year-based”, “month-based” and “week-based” user/non-user.

Linear discriminates for user/non-user separation is evaluated by several methods, here we will consider the following Relations:

For users:

$$Th + \sum k_i CT > 0 \tag{10}$$

For non users:

$$Th + \sum k_i CT \le 0 \tag{11}$$

Where

Th : is the thresholds.

CT : is the conditional attributes.

k_i : are the coefficients of the conditional attributes.

Data had been taken from the database which was collected by Elaine Fehrman [22] for 21 different types of legal and illegal drugs separately, where the values of the five factors (N, E, O, A, C) in addition to Impulsivity (Imp) and Sensation-Seeking (SS) as well as biographical data: age, gender, and education are used as the conditional attributes in the decision table shown in Table I.

Now, we will use rough sets methodology to find structural connections within the given data to obtain all reducts and finally a set of generalized classification rules are extracted to predict the drug user/non-user. The overall steps of the suggested rough sets methodology are shown in Fig. 2.

By using RST analysis toolkit software called ROSETTA where Semi-Naïve algorithm were used to discretize the data in Table I to be as shown in Table II where “ * means do not care condition” . After that reduction techniques based rough sets is used to determine the minimal reducts of (factors) attributes that can characterize all the knowledge in the decision tables as presented in Table III. Finally, the knowledge gained from all extracted reducts can be outlined by rough sets dependency rules as shown in Table IV.

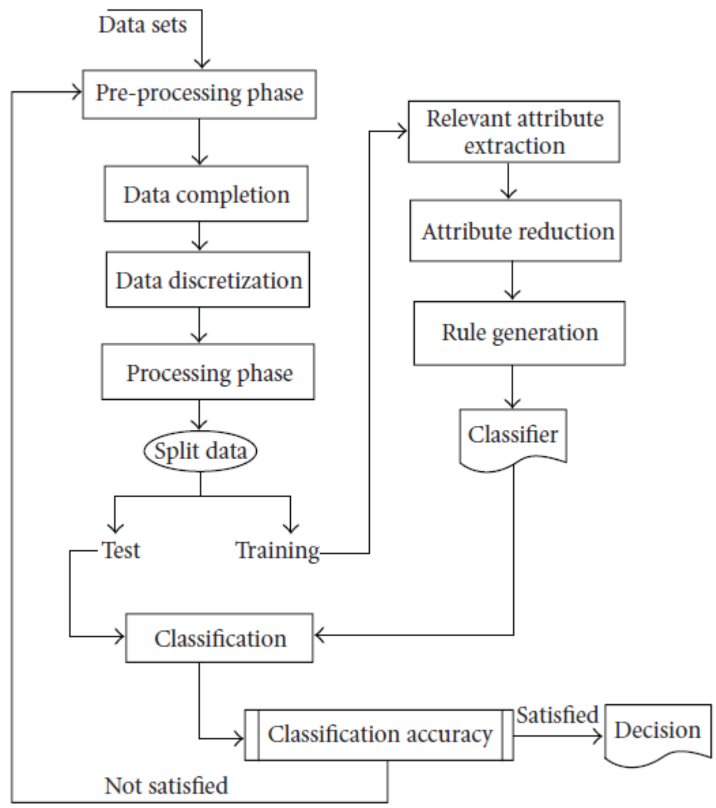

Fig. 2. The Overall Steps of the Suggested Rough Sets Methodology.

TABLE I. Decision Table of Coefficients of Linear Discriminant for User/Non-user (Year-based user Definition)

	TH	Age	Gndr	Edu	N	E	O	A	C	Imp	SS	Drug
x1	0.130	0.263	0.058	0.590	0.096	0.588	0.111	0.078	0.083	0.193	0.402	Alcohol
x2	0.543	0.643	0.293	0.249	0.063	0.176	0.347	0.103	0.201	0.241	0.418	Amphetamines
x3	0.821	0.361	0.365	0.229	0.223	0.114	0.178	0.144	0.018	0.088	0.749	Amyl nitrite
x4	0.416	0.115	0.292	0.243	0.711	0.128	0.284	0.180	0.072	0.167	0.418	Benz.
x5	0.122	0.542	0.250	0.394	0.132	0.166	0.547	0.037	0.132	0.015	0.355	Cannabis
x6	0.132	0.138	0.501	0.284	0.161	0.107	0.379	0.004	0.440	0.488	0.193	Chocolate
x7	0.597	0.624	0.270	0.029	0.345	0.212	0.007	0.305	0.054	0.062	0.523	Cocaine
x8	0.273	0.019	0.042	0.369	0.261	0.637	0.043	0.035	0.239	0.424	0.385	Caffeine

x9	0.836	0.154	0.555	0.131	0.449	0.114	0.075	0.253	0.156	0.076	0.581	Crack
x10	0.633	0.820	0.257	0.047	0.139	0.093	0.284	0.123	0.165	0.028	0.328	Ecstasy
x11	1.037	0.560	0.226	0.371	0.181	0.350	0.159	0.397	0.016	0.368	0.154	Heroin
x12	0.793	0.776	0.386	0.020	0.097	0.147	0.340	0.098	0.268	0.039	0.139	Ketamine
x13	0.693	0.519	0.467	0.224	0.012	0.190	0.409	0.136	0.240	0.022	0.427	Legal highs
x14	0.851	0.722	0.284	0.173	0.006	0.045	0.541	0.007	0.032	0.098	0.252	LSD
x15	0.551	0.404	0.296	0.259	0.262	0.443	0.417	0.270	0.105	0.003	0.399	Methadone
x16	0.764	0.594	0.267	0.233	0.184	0.236	0.604	0.019	0.066	0.070	0.239	MMushrooms
x17	0.019	0.461	0.283	0.530	0.092	0.037	0.318	0.013	0.375	0.157	0.389	Nicotine
x18	1.027	0.785	0.222	0.003	0.081	0.059	0.174	0.215	0.073	0.096	0.482	VSA
x19	0.545	0.525	0.364	0.187	0.301	0.180	0.224	0.295	0.013	0.129	0.530	Heroin pleiad
x20	0.019	0.576	0.241	0.339	0.133	0.207	0.514	0.098	0.172	0.073	0.355	Ecstasy pleiad
x21	0.346	0.309	0.380	0.254	0.479	0.125	0.274	0.215	0.123	0.171	0.534	Benz. pleiad

TABLE II. DECISION TABLE OF COEFFICIENTS OF LINEAR DISCRIMINANT FOR USER/NON-USER (YEAR-BASED USER DEFINITION)

	TH	**Age**	**Gndr**	**Edu**	**N**	**E**	**O**	**A**	**C**	**Imp**	**SS**	**Drug**
x1	[0.075, 0.131)	[-0.286, -0.189)	[0.050, 0.280)	[0.480, *)	[0.094, 0.139)	[0.400, 0.613)	[-0.144, -0.093)	[0.057, *)	[-0.094, -0.074)	[-0.340, -0.145)	[0.401, 0.410)	Alcohol
x2	[-0.544, -0.479)	[-0.682, -0.633)	[-0.294, -0.292)	[-0.251, -0.246)	[0.035, 0.072)	[-0.178, -0.171)	[0.344, 0.363)	[-0.113, -0.100)	[-0.220, -0.186)	[0.206, 0.305)	[0.410, 0.423)	Amphetamines
x3	[-0.828, -0.807)	[-0.382, -0.335)	[-0.372, -0.364)	[-0.231, -0.226)	[*, -0.203)	[-0.119, -0.079)	[*, -0.144)	[-0.162, -0.140)	[-0.025, -0.002)	[-0.093, -0.063)	[0.665, *)	Amyl nitrite
x4	[-0.479, -0.381)	[-0.189, -0.067)	[-0.292, -0.288)	[-0.246, -0.238)	[0.595, *)	[-0.137, -0.126)	[0.279, 0.301)	[-0.197, -0.162)	[0.063, 0.073)	[0.162, 0.169)	[0.410, 0.423)	Benz.
x5	[-0.234, -0.070)	[-0.551, -0.533)	[-0.253, -0.245)	[-0.462, -0.382)	[-0.132, -0.114)	[-0.171, -0.156)	[0.544, 0.576)	[-0.067, -0.028)	[-0.148, -0.127)	[0.009, 0.019)	[0.342, 0.370)	Cannabis
x6	[0.131, 0.203)	[0.060, 0.146)	[0.280, *)	[-0.311, -0.271)	[-0.172, -0.150)	[0.100, 0.160)	[0.363, 0.394)	[-0.011, 0.002)	[*, -0.407)	[*, -0.340)	[0.174, 0.216)	Chocolate
x7	[-0.615, -0.574)	[-0.633, -0.609)	[-0.276, -0.268)	[0.025, 0.038)	[0.323, 0.397)	[0.160, 0.400)	[-0.025, 0.076)	[-0.351, -0.300)	[0.035, 0.063)	[0.042, 0.066)	[0.503, 0.527)	Cocaine
x8	[0.203, *)	[-0.067, 0.060)	[-0.090, 0.050)	[0.208, 0.480)	[0.221, 0.262)	[0.613, *)	[-0.059, -0.025)	[0.024, 0.057)	[-0.239, -0.220)	[0.396, *)	[0.370, 0.387)	Caffeine
x9	[-0.843, -0.828)	[0.146, *)	[*, -0.511)	[-0.152, -0.064)	[0.397, 0.464)	[-0.119, -0.079)	[-0.093, -0.059)	[-0.261, -0.234)	[0.115, *)	[0.075, 0.086)	[0.558, 0.665)	Crack
x10	[-0.663, -0.615)	[*, -0.802)	[-0.262, -0.253)	[0.038, 0.208)	[-0.150, -0.136)	[0.076, 0.100)	[0.279, 0.301)	[-0.129, -0.113)	[-0.168, -0.148)	[-0.033, -0.012)	[0.290, 0.342)	Ecstasy
x11	[*, -1.032)	[-0.568, -0.551)	[-0.233, -0.224)	[-0.382, -0.355)	[0.139, 0.221)	[-0.396, -0.293)	[0.076, 0.167)	[*, -0.351)	[0.015, 0.035)	[0.305, 0.396)	[0.147, 0.174)	Heroin
x12	[-0.807, -0.778)	[-0.780, -0.749)	[-0.426, -0.383)	[0.012, 0.025)	[-0.114, -0.054)	[-0.156, -0.137)	[0.329, 0.344)	[-0.100, -0.067)	[-0.321, -0.254)	[-0.063, -0.033)	[*, 0.147)	Ketamine
x13	[-0.728, -0.663)	[-0.522, -0.490)	[-0.511, -0.426)	[-0.226, -0.205)	[-0.054, -0.003)	[-0.198, -0.185)	[0.394, 0.413)	[-0.140, -0.129)	[-0.254, -0.239)	[0.019, 0.042)	[0.423, 0.455)	Legal highs
x14	[-0.939, -0.843)	[-0.749, -0.682)	[-0.288, -0.283)	[-0.180, -0.152)	[-0.003, 0.035)	[-0.079, -0.004)	[0.528, 0.544)	[0.002, 0.010)	[-0.049, -0.025)	[-0.145, -0.093)	[0.246, 0.290)	LSD
x15	[-0.574, -0.548)	[-0.432, -0.382)	[-0.330, -0.294)	[-0.271, -0.256)	[0.262, 0.282)	[*, -0.396)	[0.413, 0.466)	[-0.282, -0.261)	[-0.114, -0.094)	[-0.012, 0.009)	[0.394, 0.401)	Methadone
x16	[-0.778, -0.728)	[-0.609, -0.585)	[-0.268, -0.262)	[-0.238, -0.231)	[-0.203, -0.172)	[-0.293, -0.221)	[0.576, *)	[-0.028, -0.011)	[-0.074, -0.049)	[0.066, 0.072)	[0.216, 0.246)	MMushrooms
x17	[-0.070, 0.000)	[-0.490, -0.432)	[-0.283, -0.276)	[*, -0.462)	[0.087, 0.094)	[-0.004, 0.048)	[0.301, 0.329)	[0.010, 0.024)	[-0.407, -0.321)	[0.143, 0.162)	[0.387, 0.394)	Nicotine
x18	[-1.032, -0.939)	[-0.802, -0.780)	[-0.224, -0.090)	[-0.064, 0.012)	[0.072, 0.087)	[0.048, 0.076)	[0.167, 0.199)	[-0.234, -0.197)	[0.073, 0.115)	[0.086, 0.113)	[0.455, 0.503)	VSA
x19	[-0.548, -0.544)	[-0.533, -0.522)	[-0.364, -0.330)	[-0.205, -0.180)	[0.282, 0.323)	[-0.185, -0.178)	[0.199, 0.249)	[-0.300, -0.282)	[-0.002, 0.015)	[0.113, 0.143)	[0.527, 0.532)	Heroin pleiad
x20	[0.000, 0.075)	[-0.585, -0.568)	[-0.245, -0.233)	[-0.355, -0.311)	[-0.136, -0.132)	[-0.221, -0.198)	[0.466, 0.528)	[-0.100, -0.067)	[-0.186, -0.168)	[0.072, 0.075)	[0.342, 0.370)	Ecstasy pleiad
x21	[-0.381, -0.234)	[-0.335, -0.286)	[-0.383, -0.372)	[-0.256, -0.251)	[0.464, 0.595)	[-0.126, -0.119)	[0.249, 0.279)	[-0.234, -0.197)	[-0.127, -0.114)	[0.169, 0.206)	[0.532, 0.558)	Benz. pleiad

TABLE III. REDUCTS OF DISCRETIZED DECISION TABLE

Reduct	{Imp }	{ TH }	{C}	{Age}	{Gndr }	{Edu}	{N}
Support	100	100	100	100	100	100	100
Length	1	1	1	1	1	1	1
Reduct	{E, O }	{E, SS }	{A, SS }	{O,A}	{E,A}	{O, SS }	
Support	100	100	100	100	100	100	
Length	2	2	2	2	2	2	

TABLE IV. THE SET OF GENERATED RULES

Rule	**LHS Support**	**RHS Support**	**RHS Accuracy**	**LHS Coverage**	**RHS Stability**
O([-0.025, 0.076)) AND SS([0.503, 0.527)) => Drug (Cocaine)	1	1	1.0	0.043478	1.0
O([-0.059, -0.025)) AND SS([0.370, 0.387)) => Drug (Caffeine)	1	1	1.0	0.043478	1.0
O([-0.093, -0.059)) AND SS([0.558, 0.665)) => Drug (Crack)	1	1	1.0	0.043478	1.0
O([0.279, 0.301)) AND SS([0.290, 0.342)) => Drug (Ecstasy)	1	1	1.0	0.043478	1.0
O([0.076, 0.167)) AND SS([0.147, 0.174)) => Drug (Heroin)	1	1	1.0	0.043478	1.0
O([0.329, 0.344)) AND SS([*, 0.147)) => Drug (Ketamine)	1	1	1.0	0.043478	1.0
O([0.301, 0.329)) AND SS([0.387, 0.394)) => Drug (Nicotine)	1	1	1.0	0.043478	1.0
O([0.167, 0.199)) AND SS([0.455, 0.503)) => Drug (VSA)	1	1	1.0	0.043478	1.0
O([0.199, 0.249)) AND SS([0.527, 0.532)) => Drug (Heroin pleiad)	1	1	1.0	0.043478	1.0
E ([-0.178, -0.171)) AND A([-0.113, -0.100)) => Drug (Amphetamines)	1	1	1.0	0.043478	1.0
E ([-0.119, -0.079)) AND A([-0.162, -0.140)) => Drug (Amyl nitrite)	1	1	1.0	0.043478	1.0
E ([-0.137, -0.126)) AND A([-0.197, -0.162)) => Drug (Benz.)	1	1	1.0	0.043478	1.0
E ([-0.171, -0.156)) AND A([-0.067, -0.028)) => Drug (Cannabis)	1	1	1.0	0.043478	1.0
E ([0.100, 0.160)) AND A([-0.011, 0.002)) => Drug (Chocolate)	1	1	1.0	0.043478	1.0
E ([0.160, 0.400)) AND A([-0.351, -0.300)) => Drug (Cocaine)	1	1	1.0	0.043478	1.0
E ([0.613, *)) AND A([0.024, 0.057)) => Drug (Caffeine)	1	1	1.0	0.043478	1.0
O([0.076, 0.167)) AND A([*, -0.351)) => Drug (Heroin)	1	1	1.0	0.043478	1.0
O([0.329, 0.344)) AND A([-0.100, -0.067)) => Drug (Ketamine)	1	1	1.0	0.043478	1.0
O([0.394, 0.413)) AND A([-0.140, -0.129)) => Drug (Legal highs)	1	1	1.0	0.043478	1.0
O([0.528, 0.544)) AND A([0.002, 0.010)) => Drug (LSD)	1	1	1.0	0.043478	1.0
O([0.413, 0.466)) AND A([-0.282, -0.261)) => Drug (Methadone)	1	1	1.0	0.043478	1.0
O([0.576, *)) AND A([-0.028, -0.011)) => Drug (MMushrooms)	1	1	1.0	0.043478	1.0
O([0.301, 0.329)) AND A([0.010, 0.024)) => Drug (Nicotine)	1	1	1.0	0.043478	1.0
O([0.167, 0.199)) AND A([-0.234, -0.197)) => Drug (VSA)	1	1	1.0	0.043478	1.0
O([0.199, 0.249)) AND A([-0.300, -0.282)) => Drug (Heroin pleiad)	1	1	1.0	0.043478	1.0
O([0.466, 0.528)) AND A([-0.100, -0.067)) => Drug (Ecstasy pleiad)	1	1	1.0	0.043478	1.0
O([0.249, 0.279)) AND A([-0.234, -0.197)) => Drug (Benz. pleiad)	1	1	1.0	0.043478	1.0
A([0.057, *)) AND SS([0.401, 0.410)) => Drug (Alcohol)	1	1	1.0	0.043478	1.0
A([-0.113, -0.100)) AND SS([0.410, 0.423)) => Drug (Amphetamines)	1	1	1.0	0.043478	1.0
A([-0.162, -0.140)) AND SS([0.665, *)) => Drug (Amyl nitrite)	1	1	1.0	0.043478	1.0
A([-0.197, -0.162)) AND SS([0.410, 0.423)) => Drug (Benz.)	1	1	1.0	0.043478	1.0
A([-0.351, -0.300)) AND SS([0.503, 0.527)) => Drug (Cocaine)	1	1	1.0	0.043478	1.0
A([0.024, 0.057)) AND SS([0.370, 0.387)) => Drug (Caffeine)	1	1	1.0	0.043478	1.0

A([-0.261, -0.234)) AND SS([0.558, 0.665)) => Drug (Crack)	1	1	1.0	0.043478	1.0
A([-0.129, -0.113)) AND SS([0.290, 0.342)) => Drug (Ecstasy)	1	1	1.0	0.043478	1.0
A([*, -0.351)) AND SS([0.147, 0.174)) => Drug (Heroin)	1	1	1.0	0.043478	1.0
A([-0.100, -0.067)) AND SS([*, 0.147)) => Drug (Ketamine)	1	1	1.0	0.043478	1.0
A([-0.140, -0.129)) AND SS([0.423, 0.455)) => Drug (Legal highs)	1	1	1.0	0.043478	1.0
E ([-0.396, -0.293)) AND SS([0.147, 0.174)) => Drug (Heroin)	1	1	1.0	0.043478	1.0
E ([-0.156, -0.137)) AND SS([*, 0.147)) => Drug (Ketamine)	1	1	1.0	0.043478	1.0
E ([-0.198, -0.185)) AND SS([0.423, 0.455)) => Drug (Legal highs)	1	1	1.0	0.043478	1.0
E ([-0.079, -0.004)) AND SS([0.246, 0.290)) => Drug (LSD)	1	1	1.0	0.043478	1.0
E ([-0.004, 0.048)) AND SS([0.387, 0.394)) => Drug (Nicotine)	1	1	1.0	0.043478	1.0
E ([-0.156, -0.137)) AND O([0.329, 0.344)) => Drug (Ketamine)	1	1	1.0	0.043478	1.0
E ([-0.198, -0.185)) AND O([0.394, 0.413)) => Drug (Legal highs)	1	1	1.0	0.043478	1.0
E ([-0.079, -0.004)) AND O([0.528, 0.544)) => Drug (LSD)	1	1	1.0	0.043478	1.0
E ([*, -0.396)) AND O([0.413, 0.466)) => Drug (Methadone)	1	1	1.0	0.043478	1.0
E ([-0.293, -0.221)) AND O([0.576, *)) => Drug (MMushrooms)	1	1	1.0	0.043478	1.0
E ([-0.004, 0.048)) AND O([0.301, 0.329)) => Drug (Nicotine)	1	1	1.0	0.043478	1.0
E ([0.400, 0.613)) AND O([-0.144, -0.093)) => Drug (Alcohol)	1	1	1.0	0.043478	1.0
E ([-0.178, -0.171)) AND O([0.344, 0.363)) => Drug (Amphetamines)	1	1	1.0	0.043478	1.0
E ([-0.119, -0.079)) AND O([*, -0.144)) => Drug (Amyl nitrite)	1	1	1.0	0.043478	1.0
N([0.094, 0.139)) => Drug (Alcohol)	1	1	1.0	0.043478	1.0
N([0.035, 0.072)) => Drug (Amphetamines)	1	1	1.0	0.043478	1.0
N([*, -0.203)) => Drug (Amyl nitrite)	1	1	1.0	0.043478	1.0
N([0.595, *)) => Drug (Benz.)	1	1	1.0	0.043478	1.0
N([-0.132, -0.114)) => Drug (Cannabis)	1	1	1.0	0.043478	1.0
N([-0.172, -0.150)) => Drug (Chocolate)	1	1	1.0	0.043478	1.0
N([0.323, 0.397)) => Drug (Cocaine)	1	1	1.0	0.043478	1.0
N([0.221, 0.262)) => Drug (Caffeine)	1	1	1.0	0.043478	1.0
Edu([0.480, *)) => Drug (Alcohol)	1	1	1.0	0.043478	1.0
Edu([-0.251, -0.246)) => Drug (Amphetamines)	1	1	1.0	0.043478	1.0
Edu([-0.231, -0.226)) => Drug (Amyl nitrite)	1	1	1.0	0.043478	1.0
Edu([-0.246, -0.238)) => Drug (Benz.)	1	1	1.0	0.043478	1.0
Edu([0.208, 0.480)) => Drug (Caffeine)	1	1	1.0	0.043478	1.0
Edu([-0.152, -0.064)) => Drug (Crack)	1	1	1.0	0.043478	1.0
Age([-0.522, -0.490)) => Drug (Legal highs)	1	1	1.0	0.043478	1.0
Age([-0.749, -0.682)) => Drug (LSD)	1	1	1.0	0.043478	1.0
Age([-0.432, -0.382)) => Drug (Methadone)	1	1	1.0	0.043478	1.0
Age([-0.585, -0.568)) => Drug (Ecstasy pleiad)	1	1	1.0	0.043478	1.0
Age([-0.335, -0.286)) => Drug (Benz. pleiad)	1	1	1.0	0.043478	1.0
C ([-0.220, -0.186)) => Drug (Amphetamines)	1	1	1.0	0.043478	1.0
C ([-0.025, -0.002)) => Drug (Amyl nitrite)	1	1	1.0	0.043478	1.0
C ([0.063, 0.073)) => Drug (Benz.)	1	1	1.0	0.043478	1.0
C ([-0.148, -0.127)) => Drug (Cannabis)	1	1	1.0	0.043478	1.0
C ([*, -0.407)) => Drug (Chocolate)	1	1	1.0	0.043478	1.0
C ([0.035, 0.063)) => Drug (Cocaine)	1	1	1.0	0.043478	1.0
C ([0.015, 0.035)) => Drug (Heroin)	1	1	1.0	0.043478	1.0

C ([-0.321, -0.254)) => Drug (Ketamine)	1	1	1.0	0.043478	1.0
Imp([0.113, 0.143)) => Drug (Heroin pleiad)	1	1	1.0	0.043478	1.0
Imp([0.072, 0.075)) => Drug (Ecstasy pleiad)	1	1	1.0	0.043478	1.0
Imp([0.169, 0.206)) => Drug (Benz. pleiad)	1	1	1.0	0.043478	1.0
Imp(Undefined) => Drug (Undefined)	1	1	1.0	0.043478	1.0
TH([0.075, 0.131)) => Drug (Alcohol)	1	1	1.0	0.043478	1.0
TH([-0.544, -0.479)) => Drug (Amphetamines)	1	1	1.0	0.043478	1.0
TH([-0.828, -0.807)) => Drug (Amyl nitrite)	1	1	1.0	0.043478	1.0
TH([-0.615, -0.574)) => Drug (Cocaine)	1	1	1.0	0.043478	1.0
TH([0.203, *)) => Drug (Caffeine)	1	1	1.0	0.043478	1.0
TH([-0.843, -0.828)) => Drug (Crack)	1	1	1.0	0.043478	1.0
TH([-0.663, -0.615)) => Drug (Ecstasy)	1	1	1.0	0.043478	1.0
TH([*, -1.032)) => Drug (Heroin)	1	1	1.0	0.043478	1.0

TABLE V. DRUG GROUPS ACCORDING TO THE VALUES WHICH DIFFER FROM THE SAMPLE MEAN FOR GROUPS OF USERS FOR THE MONTH-BASED USER/NON-USER

Group No.		**N**	**E**	**O**	**A**	**C**
1	Alcohol, Chocolate, Caffeine	Neutral value (i.e. all factors for these legal drug consumers does not significantly differ from the sample mean)				
2	Nicotine	high	Neutral	high	Neutral	low
3	Amphetamines, Ketamine, and Legal highs	high	Neutral	high	low	low
4	Ecstasy and LSD	Neutral	high	high	low	low
5	Amyl nitrite	Neutral	Neutral	Neutral	low	low
6	Cannabis and Magic Mushrooms	Neutral	Neutral	high	low	low
7	Benzodiazepines, Heroin, and Methadone	high	low	high	low	low
8	Crack	high	low	Neutral	low	low
9	Cocaine and VSA	high	high	high	low	low

As shown in Table IV, the extracted decision rules represent the influence of the personality traits on the risk of drug consumption. For drug users, it is found that the N and O values of are moderately high or neutral, while the value of A and C are moderately low or neutral. In general we can call that, the risk of drug consumption increases as the values of “N” and “O” increase , while the risk decreases as there is an increase in the values of “A” and “C”. So we can conclude that drug users (month-based user definition) have higher values of on N and O, and lower on A and C when compared to drug non-users (month-based user definition). The impact of the values of “E” is cannot be generalized i.e. specific. Also, all drugs can be separated into nine groups according to the values which differ from the sample mean for groups of users for the month-based user/non-user as shown in Table V.

IV. CONCLUSION

This work used the principles of rough set theory to find and explain the relationship between drug use and personality traits, impulsivity, and sensation seeking, by generating a set of decision rules to investigate and predict the impact of the personality traits on drug user/Non-user (month-based user definition). It is concluded that for drug users, the N and O values of are moderately high or neutral, while the value of A and C are moderately low or neutral. These results demonstrate the novelty of the current work which can be summarized as the suggested methodology has simplified logic-based rules required to effectively analyse drug abuse, construct a knowledge base with high accuracy to analyze drug misuse successfully and may be valuable in many applications. The future work will be extended by using other intelligent systems like neural networks, genetic algorithms, fuzzy approaches, and so forth.

ACKNOWLEDGMENT

“This work was supported by the Deanship of Scientific Research at Prince Sattam bin Abdulaziz University under the research project (PSAU-2022/02/20334)”

CONFLICTS OF INTEREST

“The authors declare no conflict of interest “

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