Journal of Scientific & Industrial Research
Vol. 80, July 2021, pp. 593-599

Classification of Addiction Behavior based on Regular and Rare Model

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Received 21 December 2020; revised 21 June 2021; accepted 22 June 2021

Realization is the comprehension of existence in its widest terms. Many of us, both physically and virtually, are unconscious of our level of addictive concern. Predicting virtual and emotional-based activity poses certain difficulties in determining an addiction level. Specifically, how to compute the addictive and what types of controls can help us monitor the addiction and get a good estimate of the individual's addicted stage. The threshold levels vary depending on a variety of factors such as age, gender, society, and so on. The addiction mentality system's prediction plays a vital role. In this regard, our research develops a Regular and Rare (RAR) based classification model for finding effective addiction predictors. This RAR classification and prediction technique is based on an examination of addiction patterns' consistency. This strategy focuses on the length of time spent doing the same activity rather than the amount of quantity consumed. The concept behind it if an individual consumes a low density of nicotine but persists for a decade, this is considered as a habitual and addictive activity. In such a way that if an individual doesn't really engage in the very same type of activity for an extended period of time, the action may be considered an uncommon occurrences rather than an addictive class.

Keywords: Addictive preventive, Introspective system, Predictive model, Substance addiction, Virtual addiction

Introduction

Individuals suffering from substance abuse, such as opiate addiction, are prone to dysfunctional decision-making.[1] Addiction may not have been substance- or virtual-based, but it is a result of the individual's mental processes, which are influenced by a variety of factors such as peers and mass media commercials. The predictive methodology is highly essential in data science, analytics, and other fields too. When constructing a predictive model, technically interconnected and also psychologically associated factors must be examined.

Addiction is a kind of activity that is a significant concern with logically connected with emotionally bonded activity since the psychological intuitions are highly relevant to past data which leads highly influence on a decision-making system. The input of every action might be in two categories which kind of activity either rare or regular activity. The activity can be classified into deterministic or nondeterministic activity. When such behavior does not appear in historical data, it is classified as Nondeterministic and Infrequent (NR) activity. Unless NR activity becomes Deterministic and Regular (DR) activity, NR activity has very little chance of becoming addictive. A deterministic action that is carried out on a regular basis is called as DR activity. This research is aimed at how the automation model works on addictive decision-making systems.

Every human activity, such as repetitive addicted behaviour, is an uncertain occurrence in general. Because of the discrepancies between real and anticipated conceptual decisions, numerous cognitive paradoxes contribute to the formation of uncertainty.[2] To assess the level of uncertainty around addictive behaviour, an analysis must be conducted to determine whether the addictive behaviour is regular or rare. As a result of these cognitive models, psychological recommendations are suggested, and individuals can match their values to determine if they are addictive or not, which aids risk rate categorization choice systems; reflects the personal over-analysis on a dataset between the members of the datasets; rather than an isolated set of data; yields extremely effective results. When health-care systems, such as addiction systems and health-record-tracking systems, and student academic performance are both high, an activity-based decision system with an introspective modeling over a datasets could provide more valuable decisions with greater accuracy.

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Materials and Methods

Behavioral addiction, whether it is to a physical substance or to an internet-based habit, is linked to negative outcomes. In recent decades, the "broken brain" model of addiction has been increasingly popular.[3] The addict's behaviour is unaffected by conscious appraisal and control as a result of the sensory characteristics of cues.[4] The compulsive conduct is addictive physical substance use, and the content of these addictive thoughts is the need to use the drug. According to most hunger researchers, classical conditioning is the cause of these beliefs. Conditioning, for example, establishes a link between the pleasurable benefits of consuming a stimulant and the triggers that reliably predict substance availability.[5] As well the virtual, smartphone addiction is a form of online addiction.[6] From this stance, the internet-based and other virtual system based including television, gadgets, and other video relevance base interactive via the virtual user interface is known as virtual systems. Any virtual system based addiction is Virtual addiction.

Excessive and compulsive impairment is characterized as a virtual or physical substance-based addiction. The influence factors are highly imparted within as a sensitive duration of adolescence and multiple factors are influential in their addictive concern.[7] Smartphone addiction might be a huge level of information and communications and technology have negative effects on human behavior and which affects both physical as well as mental health of both the individual and society.[8] In virtual addiction mainly via the smartphone and internet addictive characters are similar and the scales. Internet addiction leads to psychological and emotional states were found to correlate with smartphone addiction to negative effects such as loneliness[9], stress.[10] These kinds of addiction affect personality traits as well as emotional and social states.[11] Training content positive things concerned generating positive effects. This might be correlated and constructing a positive initial experience within an earlier stage of the training. Information technology-based addiction such as smartphone addiction, Facebook addiction, internet addiction, and gaming based addiction is related to behavioral-based addiction as problem gambling and other substance-based addiction such as alcohol-based addiction. These types of multiple addictive issues might be synergistic and highly impair psychosocial functioning. Behavior based decision system is more essential to make self-measure about an addict or not. For that we proposed the regular and rare (RAR model) for an effective classification system. Since the introspective view analysis among the consistency about routine seeking behavior has assisted to provide effective classification of uncertainty. The core idea is that human cognition is made up of two forms of information processing: automatic and regulated (or non-automatic).[12,13] Predicting addictive patterns is more important than making a decision on an addictive action since it allows you to understand the recurrent, demanding addictive activity. The design of prediction models for data-driven and computer-assisted future event prediction is driven by the uncertainty contexts.[14]

Predictive Introspection Model

Analysis of both deterministic and non-deterministic is associated with regular and rare activity respectively. The correlative systems between addictive predictions have the following hypotheses.

(i) H1: Mapping relationships between exploring experiences with datasets input are deterministic or non-deterministic?
(ii) H2: Predictive introspective view on a dataset for classifications on rare or regular based on deterministic action?
(iii) H3: Based on Regular or Rare classification deciding on an addictive level?

Introspective Observe System

The decision on addictive or non-addictive was based solely on those contexts about rare or regular. Furthermore how these addictions are carried either deterministic regular or non-deterministic rarely event. The deterministic regular event can be analyzed by True positive and True Negative (TPR ratio) and the nondeterministic rare event can be measure by False-positive and False-negative (FPR ratio). Decision-making on the prediction system has highly required the data monitoring and relationship among the data members in the dataset which leads to highly effective results rather than loosely coupled datasets. As illustrated in Fig. 1, the introspective view on datasets is deep relationship analytics on the dataset in terms of related thing analysis of dataset members.

Deterministic vs. Non deterministic

Every action is carried on whether exploring new experiences which might be rarely or regularly.

Rarely actions might be nondeterministic and regularly might be deterministic actions. Decision making on addiction level via the analysis of dataset relationship based on that accuracy level of addictive might be derived.

H1: Mapping relationships between exploring experiences with datasets input are deterministic or non-deterministic?

Predicting Strategy Model

The model connected via the horizontal and vertical setup refers to pattern mapping with features of historic data as shown in Fig. 2. Horizontal data refers to the observing pattern process and vertical concern with historical data is in existing repositories. Cross functionality checking the above model has provided good accuracy with the decision tree algorithm. Hence the ∑ values are considered the training datasets and existing and Q's are states which are absorption state when Q closely introspective as well as cognitive tracks of datasets ∑ then they will effectively assisting in decision-making systems.

$$\sum{}^{*}Q=Q \quad \ldots(1)$$

Horizontal {a}-Observing data
Vertical {b} - Historical data

There is the term statement(X) states that like the model because of understands (TP-true positive) the model and do not likes the model due to the not understands as a statement (Y) (TN-true negative). If neither or statement (W) becomes false positive and statement(Y) as False Negative (FN). The introspective effects based on the inputs proposed to act in every state, there might be interchange events but the model of the system has provided higher accuracy in predictive systems in an addictive measure too and as shown in Table 1.

Ex: Statement W: I like the model
Statement X: I understand the model
Statement Y: I do not like the model
Statement Z: I do not understand the model

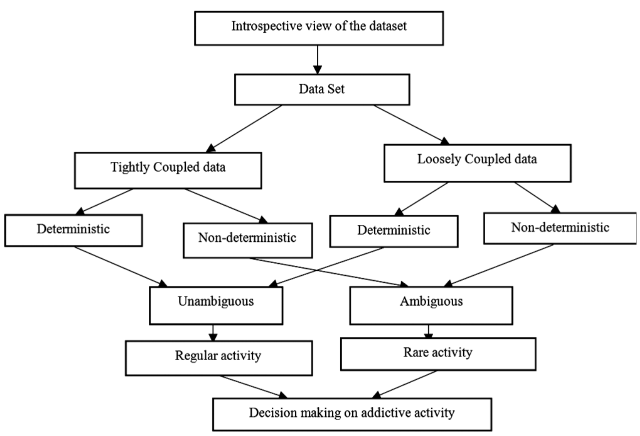

Fig. 1 — Overview of introspective observe system into on dataset

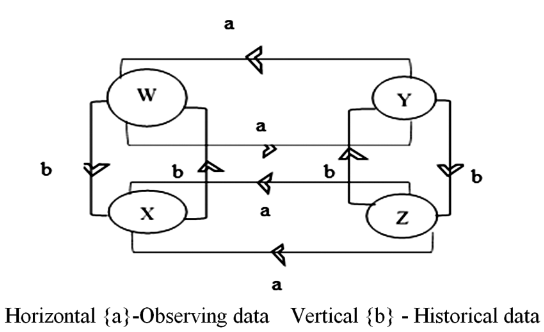

Fig. 2 — Sample Transition on dataset view

H2: Predictive introspective view on the dataset for classifications on regular andrare(RAR) based on deterministic action?

Regular and Rare (RAR) classification concern the duration of addictive activity between the last time and current. The density might be varied, person to person due to the multi-physical and environmental factors. An introspective deeply checking mechanism helps to find how tightly correlated with the dataset and analysis of the association.

Ambiguous Vs. Unambiguous

When a risky activity, like as addiction or routine seeking, occurs, classifying the decision-making process becomes a difficult assignment. There is more than one possibility to decide numerical order data set in case of either one or two options based decisions. If more possibility of either definite or infinite data set then it could be unambiguous. In numerical options-based data set offers a more accurate system rather

Table 1 — Transcript values and metrics

Introspective state	Proposition A	Proposition B	Introspective Decision
State X	I like the model	I understand the model	True Positive(TP)
State Y	I do not like the model	I do not understand the model	True Negative(TN)
State W	I like the model	I do not understand the model	False Positive(FP)
State Z	I do not like the model	I understand the model	False Negative(FN)

than more number of data members whether finite or infinite. When a dataset has a large number of choices, the same numbers of transactions are used to make an effective decision, as shown in Fig. 3. If the 'L' number of events occurs, possible inputs are Q, and then the possible decisions have to be taken for the decision process. Let L= {A,B) then the process needed to make decisions is either Q ={ok or Not (not ok} decision can be carry in L*Q actions required and represented in Table 2.

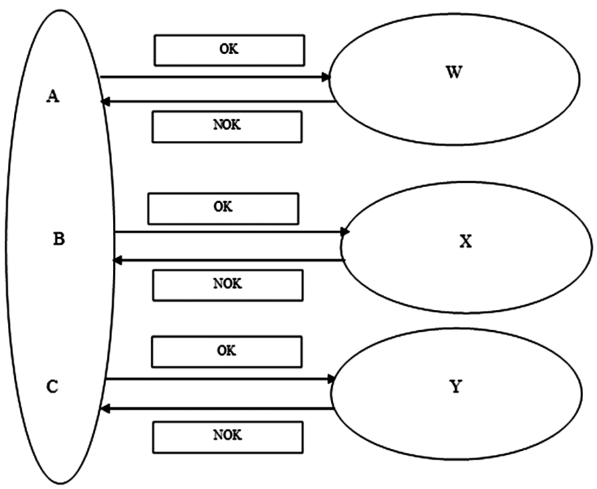

Fig. 3 — Sample representation of interdependencies among the dataset

Table 2 — Algorithm

Interdependencies based dataset relevance algorithm

Step 1: L= {A, B, C} and ‘i’ is pivot element and input values Q= (a, b), then the output R= {W, X, Y),
R□ {ok, Nok}
Step2: Init pivot ‘i’ value if A → W by a
Step 3: return ‘W=ok’ unless ‘A’ by b
Step3: else if upward pivot ’i+1’ A → X by a
Step 4: return ‘X=ok’ unless ‘A’ by b
Step5: else if upward pivot ’i+1’ A → Y by a
Step 6: return ‘Y=ok’ unless ‘A’ by b
Step7: Else if repeat j i+1 → move to B, C via a, b
Step8: Until repeat “{each transition of B, → Nok}
Unless “LR=ok”

$$\text{The Model accuracy } I_{\text{introspective}} = \frac{W+X+Y+Z}{Q}$$

$$\text{True Positive Rate TPR} = 2* \frac{TP+TN}{Q}$$

$$\text{False Positive Rate FPR} = 2* \frac{FP+FN}{Q}$$

H3: Based on Regular or Rare classification deciding on an addictive level?

When an activity becomes regular or rare, based on the input mappings such as duration, intensity of usage count, time between the first and last occurrences, the repeating activity each day or month, the activity becomes regular or rare. Based on these features and historic data comparison is the comparison of horizontal with vertical data. Addiction might be substance dependent or behavior such as watching videos, immensely playing online gaming. These both are common context about frequent based routine actions. The quantity of consumption or routine seeking behavior might vary, due to the circumstance and social factors. So consistency measure rather than quantity which provides higher accuracy about the individual is addict or non-addict in respective model of Regular or Rare. The dataset was collected from a multi addictive context which is available in open in kaggle website.

From that source sample data were used for the introspective system and the dataset, based on basic data of what kind of addiction you have? When you started this habit? How long you carry this habit? When you did last? Such basic questions were collected with demographic data (N=36). In those participants, we selectively have chosen addictive data-based selective sampling on the myriad form of addictive habits as shown in Table 3.

These are the sample features of the addictive dataset and input for predictive addictive parameters.

Table 3 — Random sampling data about addictive constraints

Addictive habits	Density /Per day	Experience started year	The period between last using	Addictive absorption	Predictive Strategy
Cigarette	5 No’s/per day	10 year back	Today morning	Deterministic event	Addictive(Regular)
Smartphone	12 hrs/per day	3 year back	15 Minutes back	Deterministic	Addictive(Regular)
Pornography watching	3 hrs /per day	2 year back	1 weak back	Non-Deterministic	Non-Addictive(Rare)
Compulsive buying	10things/Per Month	3 Year back	5 days back	Non-Deterministic	Non-Addictive(Rare)
Status Expression on social media and mobile applications	5 times/per day	3 year back	1 day back	Deterministic	Addictive(Regular)
Gaming(Online/Offline)	6 hrs/Per Day	6 year back	2 days back	Deterministic	Addictive(Regular)

Based on an introspective view such kinds of activities could effectively derive the addiction states and based on the last time used duration and other feature introspective provide more accuracy from the perspective of the prediction system.

Tightly Coupled Dataset Vs. Loosely Coupled Dataset

The relationship between the members of the dataset plays primitive impacts accurately in the absolute dataset relationship. In the dataset mainly in health care system and academic monitoring these must be considered while deciding on the machine learning system.

Experimental Setup

System configuration Intel® Core(TM) i7-7700 CPU 8GB RAM was used and online decision tree classification using Jamovi 1.1.9.0 version, open-source software, which is used and binomial tests were carried out to know the relevance of the data set as well cordiality auditing. Bayes factor was to identify the deterministic of regular and rare of nondeterministic ratio systems. Alternate hypothesis <0.05 and 95% confidence intervals are carried and the Bayes factor were calculated. Various addicting habits are taken to be considered such as physical substance (cigarette use), other virtual system-based addictive habits inclusive of compulsive buying, virtual gaming (online/offline), pornography watching, smartphone addictive, the status expression on social media, and mobile application. All such are taken into similar Bayes factor 2.85714 and lower and upper bound are 0.0000, 0.58180. The regular and rare classifications are based on the duration of recurring activity rather than the consumption density as shown in Fig. 4. These values are the same in all contexts of addiction which denotes addictive habits and density of usage those contaminants have the same values. Based on experience on comparing the experience year of habits and density were calculated, due to often happened addictive concern as by Bayes factor 0.94286 upper-bounded varied from 0.58180 to 0.72866 To deterministic 0.45714 and non deterministic 0.94286 of Bayes value and finally addictive as regular based 0.27619 and rare as non-addictive 0.94286 of Bayes value.

Results and Discussion

Due to the uncertain addiction context, measuring the addictiveness is quiet tough task. Our aim is to classify the addictive pattern based on duration of frequent recurrence. Some of the habit of behavior explicit and rare, other some might be implicit[15] and regular activity. As per our knowledge there is very limited studies about the cognitive psychometric modeling for analyzing, measuring as well prediction classification. In this connection, rule-based explicit processing and skill-based implicit systems are used in psychometric purpose.[16] As per the incentive sensitization concept, addiction results in increased dependency and routine oriented practices, which would lead to negative sequences and loss of control.[17–19] In skill or experience-based implicit is a model-used in cognitive information processing. But both of these rule and skill based classifications lack accuracy about whether the routine based behavior classification, since both are more concentrated on consumption based decision classifiers. From these models, the RAR introspective model is about the classification about addictive or not based on frequent access. So these RAR model systems deeply analyze the association among datasets and provide effective results on addictive classification prediction. The primary addictive sensation can be identified by introspective insight towards personal and inner thoughts of an individual as well as behavior forming habits. Individual inner intentions might be turned into an addiction.

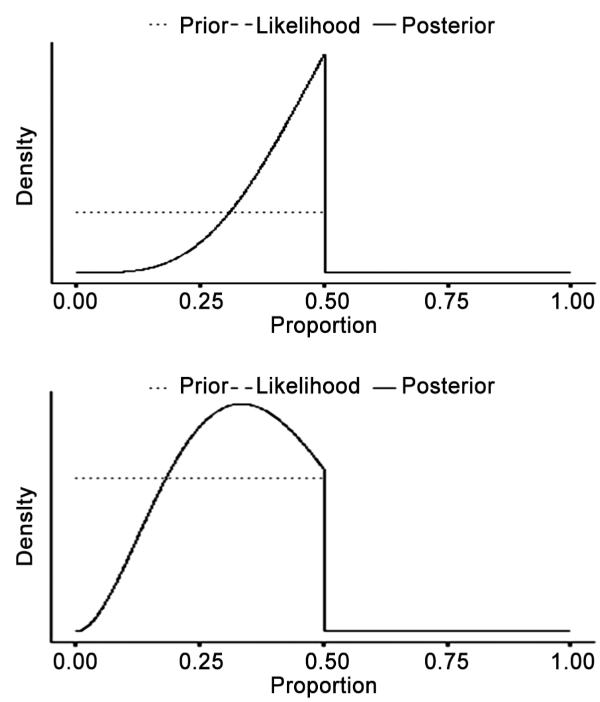

Fig. 4 — RAR based classification

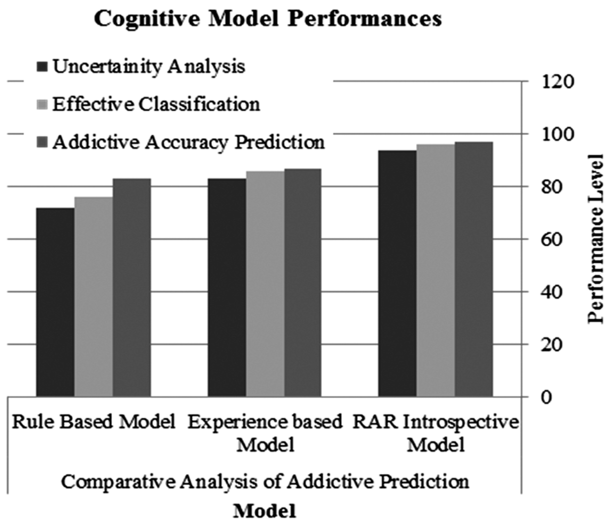

Fig. 5 — Comparative analysis of addictive predictive model

In the model representation of every level posterior plot are shown in above graph diagram and clearly shown that density towards the proportion of the various type of addictive such as smartphone, the status expression on social media, gaming, cigarette smoking, compulsive buying, pornography watching with a similar density of datasets are provided to introspective view on dataset system. Finally, addictive is a regular habit or if irregular habit that becomes a rare habit.

Comparatively this introspecting view of the dataset concerns cardinality auditing of the dataset which is highly assisting in terms of the relative data-based prediction system as shown in Fig 5. The degree of the data set might be associated with a relevant dataset. Whenever the dataset was closely coupled then the data produce a higher level of unambiguous for the effective predicting system.

According to determinacies, the dataset is how correlated occurred among the data members which need to be constraints. To an analysis of the relevancy of dataset association, the accuracy level of predictive systems is significantly improved and analysis logically connectivity with emotion bonding which supports in effective decision-making systems.

In concern with addiction, predictive measures are used for realization. The majority of people have been on addiction in terms of physical substance or virtual based addiction knowingly or unknowingly. Even repeated exposure to negative effects may not be enough to keep a substance dependent person from becoming addicted.[20] People who are subjected to high amounts of stress in their daily lives rely on social media to escape their issues and commitments, as well as to find comfort.[21,22] In this context, the predictive validated system must be evolved by taking decisions on addiction.

Conclusions

Prediction of addiction based system is a kind of emotional and physical connectivity concern. In addictive predictive measures required a deep introspective view of the dataset and the relationship among dataset has played a crucial part. To understand the relationship among given input datasets which plays a vital role in effective decision making. However the relationship of data is might be contain replicated or other duplicates, ignore such constraints, the logical connectivity of those data members greatly assists in the decisive system. Once logically trained data set, gone through this introspective model in which also effectively reduce the burden of the verification system.

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