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Machine Learning-Based Gaming Behavior Prediction Platform

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ABSTRACT

Brain disorders caused by Gaming Addiction drastically increased due to the rise of Internet users and Internet Gaming auditory. Driven by such a tendency, World Health Organization and the American Medical Association addressed this problem as a "gaming disorder" and added it to official manuals. Powerful, self-learning intelligent algorithms are suitable to predict behavior patterns and prognosis brain response depending on the addiction severity in dynamics in different conditions and stages. The current paper aims to enrich the knowledge base of the correlation between gaming activity, decision-making, and brain activation, using Machine Learning algorithms and advanced neuroimaging techniques. The proposed gaming behavior patterns prediction platform was built inside the experiment environment composed of a functional Near-Infrared Spectrometer and the computer version of Iowa Gambling Task and could benefit in diagnosing gaming disorders, their patterns, mechanisms, and abnormalities.

Keywords: Machine learning, Cognitive neuroimaging, Functional near-infrared spectroscopy, Iowa gambling task

INTRODUCTION

Internet Gaming Disorder (IGD) is an addiction that was officially admitted by American Psychiatric Association in 2013 (APA) and World Health Organization in 2018 (WHO). During the last decade, IGD affected audiences raised significantly to more than 3% in global prevalence (Stevens et al., 2021) and was already called a "new phenomenon" (Przybylski et al., 2017). Determining such a syndrome and its factors, such as depression, anxiety when the game is taken away, loss of interest in normal daily activities, education, work, family life, loss of behavior control and ability to resist the game, clinical professionals placing IGD to the same raw with substance addiction, such as cocaine or tobacco (APA, 2013). Preferring short-term rewards instead of long-term winnings and risk-acceptance strategy was used as impairment behavioral patterns in decision-making analysis named Iowa Gambling Task (Bechara and Damasio, 2002). To accelerate gaming activity, experiment participants had chosen cards one by one from four decks, followed by developed rules (Bechara et al., 1994). IGT has several dimensions used to estimate gaming decision-making impairment numerically: 1) cards have different win/loss values, and total game score can be increased or decreased depending on chosen strategy; 2) the game has 100 card choices trials conditionally separated on five blocks by 20 trials each that have different psychosomatic conditions and meanings, and 3) decks have different rewards/punishment probability and responsible for choosing short-term or long-term winning strategy (decks A and B have high rewards and loses probability and called "bad" decks; decks C and D have low rewards and loses probability, called "good' decks and preferred in terms of long-term perspective). Healthy participants begin the game in the condition of totally unknown and uncertainty (first 20 trials, block 1), understanding the game logic somewhere at the middle of the task, passing through "pre-hunch" and "hunch" conditions (trials 21-60, blocks 2 and 3), testing different winning approaches in the "conceptual" and "risky" periods (trials 61-100, blocks 4 and 5), and achieving rewards at the end, calculated in dollars and as a difference between the sum of "bad" and "good' decks (Bechara et al., 1994; Bechara and Damasio, 2004).

For more than 20 years, IGT has been used in different applications and experiments with brain disease and decision-making disorders, but in combination with modern neuroimaging techniques, such as functional magnetic resonance imaging (fMRI), functional near-infrared spectroscopy (fNIRS), electroencephalography (EEG), and others significant achievements have been made in the cognitive analysis of human brain activation during gaming and gaming behavioral biomarkers (Aram et al., 2019). Thank its invasivity, ability to provide measurements in motions, and relevant low cost, fNIRS is utilized in different applications as an extension of IGT: correlation analysis of changes in brain activity, measured as oxy-hemoglobin (HbO) levels and IGT performance (Ono et al., 2015; Li et al., 2019), effect between IGT blocks and its reflection on HbO signal measured by ANOVA in left and right brain hemispheres (Balconi et al., 2018; Kora Venu et al., 2020), t-test of HbO changes during low-risk and high-risk card selection (Bembich et al., 2018) and difference in HbO activation from participants with low and high IGT score (Suhr and Hammers, 2010). At the same time, statistical analysis methods used in these applications are based on estimation of the variables relation power and their mutual impacts and fail in less controlled experiment environments and low degree of freedom. But constructed based on "wide data," artificial Machine Learning (ML) algorithms, widely used in different applications (Aram et al., 2020; Aram et al., 2021), are suitable to predict variables health and behavior, prognosis models performance, and evaluate correlation results (Bzdok et al., 2018; Kumar and Chong, 2018). The current study proposes the intelligent ML platform to predict gaming behavioral patterns of healthy participants based on brain activation during decision-making simulation. Gaming activity will be generated by IGT and predicted by HbO signal features space. The task will be divided into five blocks and brain hemispheres to estimate differences in behavioral patterns.

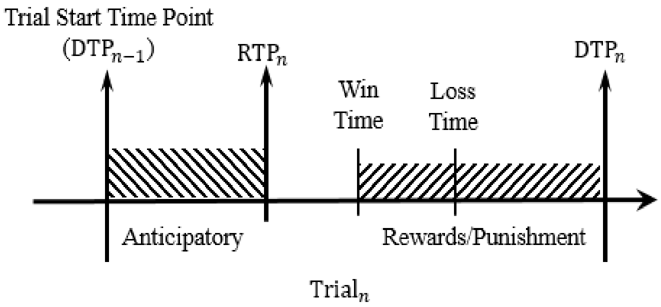

Figure 1: IGT experiment design with fNIRS synchronization time points.

METHOD

Experiment Design

Thirty young adults (25 females) in the age range 19 – 26 (M = 21.8, SD = 1.77) were hired voluntarily to participate in the data collection, approved by Southwest University (Chongqing, China) Institutional Review Board. Before the experiment, all participants reported in writing about right-handing, absence of neurological, psychiatric issues history, and problems with vision. IGT score distribution of the whole sample (N = 30) is calculated by equation (Bechara et al., 1994; Bechara and Damasio, 2004) and demonstrates the learning curve of gaming experience transition corresponding to healthy patients (Li et al., 2019; Kora Venu et al., 2020).

Following the IGT paradigm (Bechara et al., 2004), participants received $2000 virtual money before the experiment and performed 100 card choosing trials while connected to the functional near-infrared spectrometer FOIRE-3000/16 (Shimadzu Corp., Japan). The cap with 16 transmitters and 16 receivers connected by 52 channels was worn on the testee's head, covering target brain regions of interest (ROI) and positioned using Montreal Neurological Institute (MNI) standard space. Light beam propagation through human tissue in accordance with Beer-Lumber Law with wavelengths 780 nm, 805 nm, 830 nm, and frequency 4 Hz was registered by fNIRS in target ROI in the left brain hemisphere, covered by 28, 35, 36, 42, and 43 channels, and by channels 25, 32, 33, 40, and 41 in the right hemisphere for measurements stability and the result reliability. Raw data were filtered from noise, breathing, moving, or other experiment artifacts using Wavelet-MDL detrending algorithm from the NIRS-SPM software package (Ye et al., 2009).

The records of HbO were synchronized with the IGT timeline (Figure 1). For each n trial, changes of HbO levels were registered in two critical time points, responsible for gaming decision-making: 1) Reaction Time Point (RTP_n) at the end of each decision-making period, and 2) Trial Start Time Point matching with Task Duration Time Point (DTP_{n-1}) at the end of each trial. Thus, RTP_n and DTP_{n-1} are timestamps that determine boundaries of the anticipatory interval, during that experiment, participants make their card choice in accordance with the adopted strategy. The HbO signal corresponding to these points has been processed, divided by features, and used to evaluate gaming behavior prediction by the ML platform.

Features Extraction

HbO signal features space was constructed for prediction improvement in decision-making time window points RTP and DTP for the left and the right brain hemispheres (LH and RH) separately, reflecting to signal shape, distribution, average error from the actual value, etc.: 1) mean value (LHmean, RHmean); 2) variance (LHvar and RHvar); 3) standard deviation (LHsd and RHsd); 4) kurtosis (LHku and RHku); 5) skewness (LHsk and RHsk).

Machine Learning Models

ML gaming behavior prediction platform was run in R 4.0.3 (R Core Team, 2018). In the first stage, 80% of normalized HbO signal features were used for training, and 20% were used for testing ML algorithms: Multiple Regression, Classification and Regression Trees (CART), Artificial Neural Network (ANN), Support Vector Machine (SVM), and Random Forest. In the second stage, two metrics were estimated prediction accuracy: coefficient of determination (R Squared) and Root Mean Squared Error (RMSE). Lastly, classifiers with R squared closed to 1 and the lowest RMSE tested gaming behavior prediction power in each IGT block by the signal from the left and right hemispheres. ML-based gaming behavior prediction pipeline separated by the left and right brain hemispheres is presented in Figure 2.

RESULT

Performed research identified several tendencies that illustrate patterns of gaming behavior, predicted by ML-based platform (Figure 2): 1) RMSE increase from IGT block 1 to block 5 in both hemispheres; 2) R Squared decrease from IGT block 1 to block 5 in both hemispheres; 3) in each IGT block, the best model is the model with the lowest RMSE (in units of IGT score) and highest R Squared; 4) RMSE of best fitted model decrease from IGT block 1 to block 5 in both hemispheres; 5) the prediction accuracy of best fitted models more robust than training model in all IGT blocks and both hemispheres.

DISCUSSION AND CONCLUSION

The current paper and previous research (Bembich et al., 2010; Suhr and Hammers, 2010; Ono et al., 2015; Balconi et al., 2018; Li et al., 2019; Kora Venu et al., 2020) illustrate the significant difference in gaming behavioral patterns depending on participant psychosomatic condition. Pattern transfer from the uncertainty condition to certainty and risk inside IGT simulation is not smooth, not limited by blocks, and boundaries are not clearly defined. Performed research does not contradict such tendencies, but spreading pattern correlation by fNIRS signal features allows to estimate prediction power more pressingly and prognosis behavior more reliable. The ML-based platform was constructed to evaluate the correlation between brain activation and gaming activity during five conditions and both hemispheres. SVM with RBF showed one of the best accuracies: lowest RMSE 3.37 – 7.84 and highest R Squared 0.29 – 0.96 (Figure 2). The best fitted model was selected

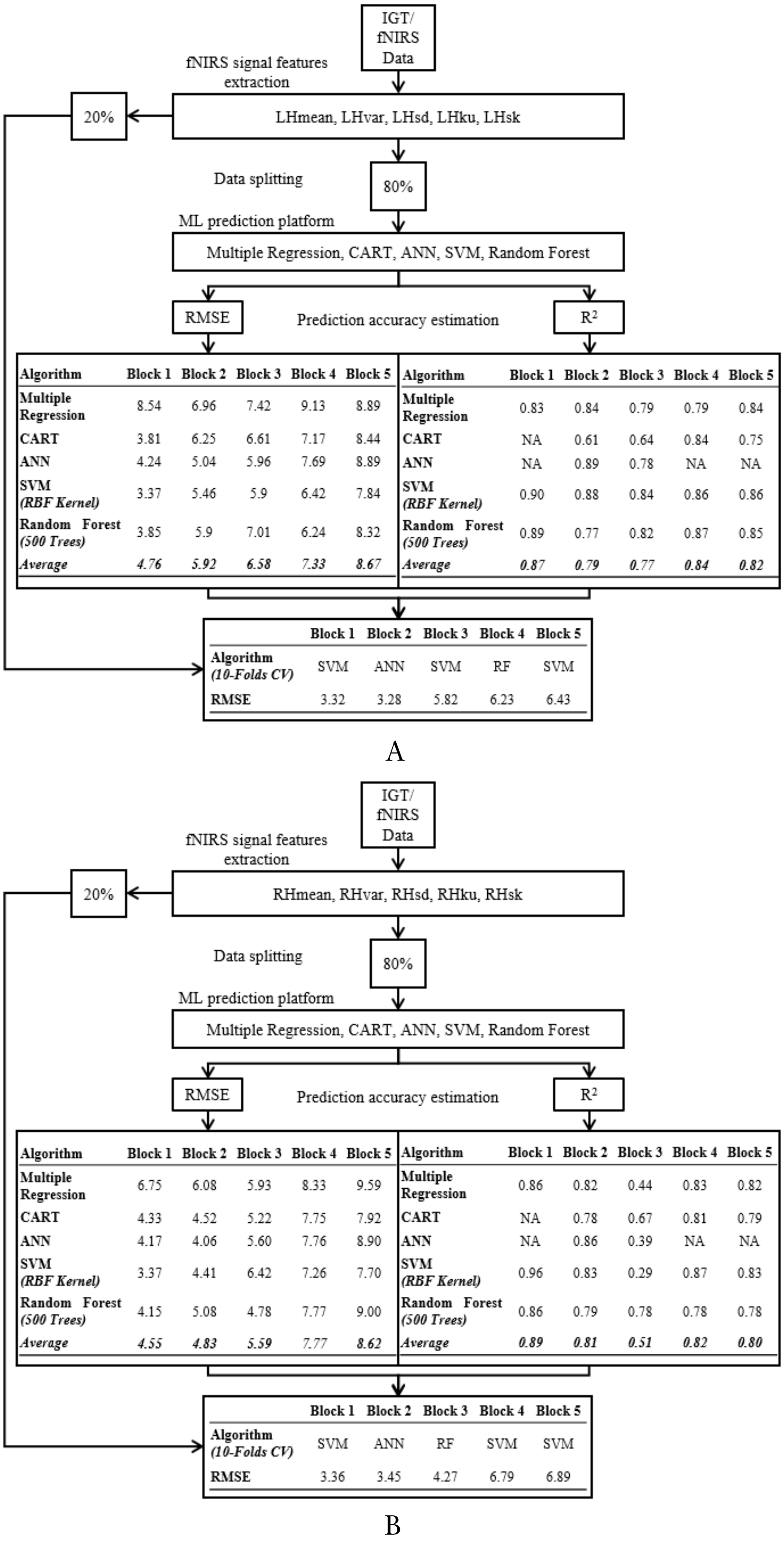

Figure 2: ML-based gaming behavior prediction pipeline: A – the left hemisphere, B – the right hemisphere.

and applied to the testing data set, showing a pattern that keeps the original learning effect transition, following healthy participants behavioral effect. Experiment participants are adding risk to decision-making, increasing the standard deviation of quantified card selection score and a measure of prediction error RMSE. The achieved mechanics illustrates the human behavioral pattern during gaming, predicted by activity in the brain.

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