A Comparative Analysis of Contact and Non-Contact Approaches Using Machine Learning for Gaming Disorder Detection

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Abstract: With the rapid development of the Internet and the gaming industry, video games have become a major form of entertainment, leading to an increase in gaming addiction, which was officially classified as a mental disorder by the World Health Organization in 2018. This article first introduces the concept and current status of gaming disorder and then reviews the application of machine learning (ML) in identifying gaming addiction, analyzing existing research on contact, e.g., Electroencephalogram (EEG), Functional Near-Infrared Spectroscopy (fNIRS), and non-contact, e.g., questionnaires, gaming data, methods. This review focuses on various machine learning techniques, such as support vector machines, random forests, and deep learning models, and their applications in improving the accuracy and efficiency of addiction diagnosis. The use of ML to study physiological signals and behavioral indicators has achieved encouraging results, although there are still limitations in the generality of the models and data acquisition methods. This article compares different ML methods, explores their advantages and limitations, and proposes potential improvements for future research on gaming disorder detection.

1 INTRODUCTION

With the continuous development of the Internet and games, games are gradually becoming a major form of entertainment for modern people. Compared with many traditional forms of entertainment, such as chess, sports, and performances, electronic games are relatively low-cost, convenient, and do not require venues. However, while the game industry is booming, although it will not cause great harm to the body, games can also cause people to have varying degrees of addiction, just like gambling, alcohol, and drugs. The World Health Organization included gaming disorders in the category of mental and behavioral disorders in 2018. Globally, the prevalence of game addiction shows a trend that the prevalence in Asia, especially in East Asia, China, Japan, and South Korea, is higher than in other regions, and the prevalence of adolescents can reach 15% (World, 2020). In terms of the proportion of patients, there are more young people than the elderly and more men than women. Game addiction will affect the physical and mental health of patients to varying degrees (Paulus, 2018). Physiological damage includes impaired vision caused by long-term use of the eyes and back problems caused by long-term sitting.

Mental health problems include difficulty sleeping and reduced self-control. Compared with non-addicts, game addicts are more likely to experience negative emotions such as depression, anxiety, and loneliness, which affects academic performance and quality of life (Dong, 2022). Therefore, from parents to schools to the government, the issue of adolescent gaming disorder is gradually being taken seriously, and different laws and regulations are being introduced to change this phenomenon. The characteristics of gaming disorder include decreased control over gaming, continuing to play games even when negative effects have occurred or are about to occur, and prioritizing gaming over other activities (Dong, 2022). From a neurobiological perspective, like other material or non-material addictions, such as alcohol and gambling, the distribution of cerebral blood flow in the brain of game addicts is different from that of normal people, and the reward mechanism and self-control area of the brain are affected. Most of the current treatment methods can be divided into drug therapy and other types of treatment. Other types of treatment include family care, psychological counseling, etc. Most drug

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therapy is used to relieve depression and anxiety to reduce the impact of addiction. However, the issue of how to treat gaming addiction has aroused heated discussions among many scholars. Some scholars believe that games are also a form of entertainment for teenagers, just like other activities, such as sports, chess cards, and comics. If the game time is long, it is not enough to determine that the player is a game addict, because if there is no game, he/she will choose other activities as substitutes to meet the needs of leisure and entertainment (Stevens, 2021). Therefore, whether from a psychological or physiological perspective, such as the self-rating scale for gaming disorder or Electroencephalogram (EEG), it is very important to accurately identify addicts and provide effective treatment.

As a powerful data analysis tool, machine learning has performed well in areas such as behavioral pattern recognition and classification tasks. It can identify potential addictive behavior patterns by analyzing many user behavior data (Jordan, 2015). This method can not only improve the efficiency of recognition but also provide real-time, data-based diagnostic support. If the original data of game players, such as EEG and their self-rating scale, can be classified and identified through machine learning models, the accuracy and efficiency of recognition will be greatly improved (Costa, 2019). Therefore, although it cannot provide direct treatment, its advantages of high efficiency and high accuracy have made machine learning gradually applied to the field of game addiction identification. Some studies have tried to apply various machine learning algorithms, such as support vector machines (SVM), random forests, deep learning, etc., to the problem of identifying game addiction, and have achieved remarkable results.

This paper aims to review existing related research. First, the application of different machine learning methods in identifying game addiction is classified. Secondly, select several studies in each application category and analyze their research methods, model types, etc. Next, analyze the results of each article and compare the advantages and disadvantages of different models. Finally, based on the author's information, supplement the deficiencies of the method or model.

2 MACHINE LEARNING-BASED DETECTION OF GAMING DISORDER

2.1 Overview

At present, the research on the degree of addiction of adolescents to online games using machine learning is mainly divided into two types, namely contact and non-contact. The contact type mostly uses the relevant model of machine learning to analyze the brain wave signal data of the subjects to determine whether they are addicted to the Internet and the severity of the degree. For non-contact game addiction research, the main method is to use machine learning models and algorithms to analyze the questionnaire results filled out by the subjects or the game-playing data of the subjects, to determine whether they are addicted to games.

2.2 Contact Gaming Disorder Detection

An existing contact machine learning game addiction judgment method Functional Near-Infrared Spectroscopy (fNIRS), namely functional Near-Infrared Spectroscopy (Bunce, 2006). According to the research of Wang Qiwen and others, they used this technology to measure the changes in the prefrontal cerebral blood oxygen concentration when the subjects' brains performed the stop signal task. Then machine learning to analyze and compare with the data of normal people to determine whether the subject is a game addict. The experimental method is to let the subjects use the left and right arrow keys on the keyboard to respond to the left and right arrows on the screen according to the requirements under interference-free conditions and use the light NIRS portable brain imaging device worn on the subject's head to use near-infrared light to monitor the changes in blood oxygen concentration in the forehead of the brain in real-time. After collecting the raw data, feature extraction was performed on it. In this study, the mean, skewness, and kurtosis were mainly extracted. Afterward, the researchers selected three machine learning classifiers and a Long Short-Term Memory (LSTM) classification model to distinguish between game addicts and healthy people. The three machine learning classifiers are SVM, Linear Discriminant Analysis (LDA), and K-Nearest Neighbors (KNN). In this experiment, their classification accuracy rates of the combined mean, skewness, and kurtosis were 67.4%, 63.6%, and

71.2%, respectively. The accuracy of the LSTM model in identifying game addicts was 85.7, which is better than the traditional machine learning method. This study shows that the combination of fNIRS signals and machine learning classification can provide powerful clinical treatment assistance for identifying whether patients are addicted to games (Cho, 2022).

Another example of a contact gaming disorder determination model was conducted by Lee et al. The original data was obtained through the EEG of the subjects in the eyes closed and eyes open state for five minutes each. After preprocessing the initial EEG signal, it was divided into multiple periods and converted into corresponding frequency bands. In terms of algorithm selection, the researchers selected three EEG-related algorithms. The researchers used cross-validation and took into account the weighted calculation of the model's bias and split probability. After multiple iterations and repetitions, the model's ability to correctly identify whether a subject is addicted to games gradually became evaluable. The results showed that compared with the unimodal model, the multimodal model is more accurate in identifying online gaming disorders. However, the researchers said that this study still has the problem of small research subjects and lack of universality of the results. And further combining deep learning algorithms and machine learning is also necessary to improve model performance (Lee, 2022).

2.3 Non-Contact Gaming Disorder Detection

There are two main types of non-contact game addiction judgment models. One is to judge by analyzing the game-playing data of students or players, such as calculating from the game time, campus network records, and student attendance. The other is to let the subjects fill out a questionnaire about game addiction using an evaluation form and judge whether the subjects are game addicts by analyzing the scores of each item.

Song's research belongs to the first category. In this model, the evaluation indicators of whether it is Internet addiction are divided into two categories: impact and daily behavior. Impact includes three subcategories: damage to physical and mental health, frustration of willpower, and failure to graduate normally. Daily behavior consists of five subcategories: the degree of attention parents pays to education, academic performance, average daily Internet time in the dormitory, class attendance, and mental health. In the model for judging Internet game disorder, each data has different data characteristics, which will greatly affect the results. The researchers used fuzzy C-means clustering to divide the data. In the calculation and evaluation stage of the data, the researchers selected the fuzzy hierarchical analysis method for quantitative and qualitative analysis and divided the degree of Internet game addiction of specific students into four levels, namely normal, mild, severe, and extremely severe. When assigning weights to each indicator, the researchers took into account the theory that multiple factors in psychology can affect people's judgments and the method theory of multi-attribute decision-making. The model uses consistency tests to perform data fuzzification and weight calculation. The fuzzy operator uses the main factor-determined Zade operator. The researchers pre-set several corresponding decisions for different game addiction severity ratings, such as psychological counseling, contacting parents, and pushing reminders. The above measures can be changed according to actual conditions. In addition, the researchers also distributed questionnaires in colleges and universities as a control for this model and classified the data filled out by each respondent into data applicable to this model. In this study, the researchers gave a more detailed data fuzzy processing calculation method, first using the Fuzzy C-Means clustering method to divide the data, and then using the fuzzy hierarchical analysis method to determine the severity of addiction. However, this study did not give a detailed questionnaire survey result for the model's assistance and machine learning process. At the same time, for some raw data that are difficult to quantitatively analyze, such as the importance of parental education, and raw data that are difficult to obtain, such as mental health, the researchers did not give detailed acquisition methods and quantitative calculation methods (Song, 2019).

The study by Kong et al. belongs to the second non-contact measurement model. They selected 2,100 students from three junior high schools and three high schools in three regions of Guizhou Province as the research subjects. The questionnaire design includes Nine-item Internet Gaming Disorder Scale-Short Form (IGDS9-SF), Parental Psychological Control and Autonomy Support Questionnaire (PPCASQ), Motivational Structure Questionnaire, Relative Deprivation Questionnaire, Deviant Peer Interaction Questionnaire and Self-Control Dual System Scale for data collection. Except for the relative deprivation questionnaire, all other questionnaires are scored using the Likert "1 to 5 points" system, and the relative deprivation questionnaire uses the Likert "1 to 6 points" system.

When the research subjects fill in the questionnaire, there are professionals to explain, so that the subjects can give more credible data with full understanding. And the diagnostic accuracy of IGDS9-SF reaches 96.1%. Based on Python, the researchers use algorithms including logistic regression, support vector machine, decision tree, gradient boosting tree, adaptive boosting algorithm, and random forest to judge and predict game addiction behavior. According to the research results, the prediction accuracy of these six methods is higher than 90%. After comprehensively considering the evaluation indicators such as precision and recall rate, the adaptive improvement model performs best. The adaptive improvement model continuously iterates to enhance the weight ratio of each item and focuses on the distribution pattern of the data with incorrect predictions to complete the correction. In this study, the prediction accuracy reached 99%. However, since only six schools in three places in Guizhou were selected in this study, the geographical scope is small, and its model may need more data training to improve universality. In addition, the method of obtaining raw data through questionnaires is more subjective than that of obtaining data from student behavior and players, so the data may be biased (Kong, 2024).

3 DISCUSSIONS

Although some machine models in some of the studies mentioned above have achieved high accuracy in detecting gaming disorders, each study may have problems to a greater or lesser extent. Although the detection accuracy of both in specific model algorithms has reached a high level, that is, more than 80%. However, in comparison, the accuracy of the non-contact model is higher than that of the contact model. This may be because the EEG data is more complicated for all Likert scales, and there are more misjudgements and data losses in the judgment process. However, the latter needs to design weights for various indicators, and there is a problem that a lot of statistical calculation modeling is required. The problem of non-contact machine model detection is more serious. For the questionnaire of the non-contact detection model, since the subjects themselves conduct self-evaluation in the questionnaire survey, for example, the scales of parental family control, self-esteem, and anxiety are difficult to quantify and there are subjective misjudgements. Therefore, this will more or less affect the original data submitted to the model for processing, thereby affecting the accuracy of the judgment. In general, both non-contact and contact models have the problem of lack of universality. Lee et al.'s EEG model study has few research subjects, so it lacks universality. Although Song's fuzzy multi-attribute college student Internet use disorder prevention and treatment platform gives a relatively detailed description of the model research and statistics, according to the author's point of view, the model is only a proposed concept. If people want to better apply this model to detect and prevent college students' game addiction, the support of the school is required. In addition, some of the data used in the study, such as Internet usage time and student attendance, may be misjudged, require various data associations within the school, and have privacy issues. More research and investigation are needed before it can be put into practical use. However, the game addiction prevention and treatment methods in this study are more than other studies, and are not the most commonly used psychological cognitive therapy for game addiction treatment, which has certain reference value. For the study by Kong et al., they selected students from six high schools in three regions of Guizhou Province for research. Although the results are relatively accurate, there will be more serious regional and age biases. For example, data from eastern and northern China, as well as college students, are not covered. However, the results given by their machine model are only relatively accurate for the existing research subjects, and the accuracy of the different models used is more than 90%. In addition, most of these studies use the game use disorder evaluation scale as a control to determine whether the machine is successful. However, as mentioned above, although the Likert scoring method in the scale assists in quantifying the scores of various data, its authenticity still needs to be investigated. But overall, most of the above machine learning models perform well. Although there are some problems, the accuracy of the model itself has been verified in the study. If there are conditions to conduct more extensive research in the future, or if there are other more accurate methods to identify game addicts as control and training data, then using machine learning to assist in identifying gaming disorders will greatly improve the efficiency and accuracy of treatment. If this technology can overcome the problems of control data and universality, then its high efficiency and high accuracy have the potential and prospects for large-scale use.

4 CONCLUSIONS

The accuracy of the machine learning models for detecting gaming disorders reviewed and analyzed above is relatively high, and they can complete basically accurate detection under experimental conditions. However, there is still room for improvement in the experimental process, and there is still a lack of more universal optimization before a large number of practical applications. At the same time, the formulation of various game time evaluation scales should also take into account practical problems such as supervisor bias. In addition, the concept of game addiction is constantly changing with the development of society and the game industry. Not everyone who plays games for too long means losing control of the game, such as e-sports practitioners. In actual applications, in order to better solve the problem of gaming disorders in society, especially for young people, in addition to complete and efficient detection methods, there should also be a good social environment and appropriate treatment methods. Current cognitive therapy can reduce dependence on games, and drug treatment can reduce anxiety and depression. However, in order to fundamentally solve the problem of gaming disorders, it requires the attention of society, schools and families. If there are complete laws as protection and abundant entertainment and sports resources as a substitute, then gaming addiction will be a fundamental treatment.

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