EEG Signal Analysis In Detecting Pornography Addiction : A Literature Review

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Abstract. The swift advancements in digital technology significantly influence addictive behaviors, and one such manifestation is pornography addiction. Pornography, aimed at serving as a means of venting sexual arousal, has led to the development of compulsive sexual activity and addiction to pornographic content. The continuous engagement with such content can have adverse effects on individuals, impacting both their health and social well-being. Within the realm of health technology, a noteworthy development is the introduction of a tool capable of delineating brain activity. The Brain-Computer Interface (BCI) stands out as a pivotal discovery in this sector, providing a communication channel between humans and external devices by decoding patterns of brain activity. Among the various methods employed in BCI, Electroencephalography (EEG) holds prominence due to its cost-effectiveness and high temporal resolution. Utilizing EEG-based BCI imagery, along with several signal processing methods, there is an anticipation that it can effectively classify individuals based on their addiction or non-addiction to pornographic content.

Keywords: Brain Computer Interface (BCI), EEG, Addiction, Pornography.

1 Introduction

An advancement in health technology is represented by the emergence of a tool capable of elucidating brain activity, known as the Brain-Computer Interface (BCI). By deciphering patterns of brain activity, the BCI establishes a communication channel between humans and external devices [1].

Due to its cost-effectiveness and superior temporal resolution, electroencephalography (EEG) stands out as one of the most commonly employed Brain-Computer Interface (BCI) technologies [2]. In EEG, electrodes are used to monitor brain activity from the scalp. The brain, with its 100 billion neurons, transmits information through neuron firing. EEG electrodes detect alterations in the electrical potential of neurons. Each electrode is labeled with a letter denoting the location of a lobe and a number or another letter for specifying the hemispheric area, whether on the right or left side of the scalp. The electrodes are positioned at predetermined intervals.[3].

The operational procedures of EEG-based Brain-Computer Interface (BCI) involve recording, feature extraction, and classification. In BCI applications with motor imagery, a pivotal method for feature extraction is event-related desynchronization (ERD)/event-related synchronization (ERS) analysis. The overall accuracy of EEG-based BCI motor imagery heavily relies on extracting informative aspects of the ERD/ERS pattern corresponding to a specific body part [4].

Pornography is the portrayal of sexual subjects with the intent of serving as a means of venting sexual arousal. Pornography addiction entails an addiction to compulsive sexual activity combined with the consumption of pornographic content, irrespective of its adverse impact on the individual's physical, mental, social, or financial well-being. Pornographic content is accessible through various mediums, including electronic media, print media, and the internet [3]. According to data released by "Pornhub," one of the world's most popular porn sites, there were over 42 billion visits to its website in 2019 [5].

Exposure to pornographic content has been linked to an increased incidence of sexual violence, including cases of harassment and rape. Approximately 40 percent of the 28 percent of women who have experienced sexual violence reported that pornography played a role in the incidents of harassment they encountered. In some instances, the perpetrator had watched pornography before harassing the woman, in others, the abuser used pornography during the harassment, and in further cases, the perpetrator coerced the victim into participating in the creation of a pornographic film [6].

Numerous researchers have explored this research topic, but only a few have delved into specific discussions (pornography addiction). This literature review aims to identify and analyze recent research on detecting pornography addiction through a comprehensive literature review.

2 Methodology

2.1 Review Method

This paper examines numerous research works pertaining to EEG Signal Analysis in the Detection of Pornography Addiction. The literature review process involves three stages: the planning stage, conduction stage, and reporting stage.

In the initial stage, the focus is on determining the materials required for the literature study. The writer sought extensive information on the utilization of Brain-Computer Interfaces (BCI) in various scenarios. Subsequently, the focus was refined to the use of brain-computer interfaces, specifically EEG-based BCI, in the identification of pornography addiction. To narrow the scope of the study, the writer developed a review protocol outlining research questions, literature sources, search strategy, selection criteria, data extraction methods, and synthesis procedures.

The conduction stage follows, where the literature review is executed using the established review protocol. This phase encompasses conducting searches, collecting, selecting, and extracting necessary resources, and then synthesizing the literature. The final step involves formatting the report according to the Springer proceeding format.

2.2 Research Questions

The following research questions might be used as a guide to keep the reviews on track:

1. RQ1: What are the impacts of pornography addiction?
2. RQ2: How is the collection of EEG signal data related to detecting pornography addiction?
3. RQ3: What kind of method are mostly used to analyze the EEG Signals in relation to detecting pornography addiction?

To investigate the research query, a thorough analysis of the entire content of the chosen publications will be conducted.

2.3 Search Strategy & Selection Criteria

The initial step in collecting literature involves conducting a comprehensive search for all pertinent materials related to the research topic. Initiate the search using terms such as "porn addiction," "EEG-based BCI," "pornography," and similar keywords. Platforms like IEEE Xplore, SCOPUS, Springer, and others were utilized to search and retrieve relevant literature.

Furthermore, the writer applied filters to refine the search results based on the following selection criteria. :

1. The search results are not limited to papers published between 2018 and 2023.
2. Journal and conference paper is a type of sources.

Because the research is still in its early stages, the writer selects all the related paper. There isn't any specific reselecting process.

Table 1. Selection Criteria.

Num.	Inclusion Criteria	Exclusion Criteria
1	Papers which related with Pornography addiction	Papers which unrelated with Pornography Addiction
2	Papers which related with EEG based BCI	-

3 Results

The table below presents the count of papers obtained through search results, filtered results, and the selection of papers. However, some papers were not authored but were referenced to clarify certain points in this paper. The subsequent table illustrates the outcomes of the search using the keywords "Porn Addiction" in SCOPUS.

Table 2. Number of selected papers.

Search Results	Filtered Resuls	Selected Papers
68	42	17

Implementing the review methodology detailed in the earlier section yielded the obtained results.

3.1 The Impacts of Pornography Addiction

Based on the review, nearly all of the chosen papers delve into the repercussions of pornography addiction on individuals. Despite the introduction of alternative labels such as sexual compulsivity, hypersexuality, out-of-control sexual behaviors, dysregulated pornography use, and problematic pornography use, terms like sex addiction and porn addiction persist as the most commonly employed expressions. [7] Another study addresses perceived addiction to internet pornography (PAtIP), linking it to anxiety, depression, spiritual challenges like resentment toward God and feelings of moral failure, lower self-esteem, relational difficulties, alcohol usage, and decreased sexual satisfaction, among other factors [8].

Pornography addiction may lead to Compulsive Sexual Behavior Disorder (CSBD), now recognized as an impulse control disorder in the eleventh revision of the International Classification of Diseases (ICD-11) [9]. Individuals with CSBD engage in various sexual behaviors, including masturbation, pornography consumption, phone sex, cybersex, visits to strip clubs, paid sexual services, excessive fantasizing about sex, and consensual sexual activities. While masturbation, pornography use, cybersex, having multiple sexual partners, and seeking sexual fantasies are commonly reported behaviors among people with CSBD, unsatisfying or unprotected sexual intercourse and multiple sexual partners are frequently described as problematic. Despite spending more time on the former activities, individuals with CSBD are more prone to experiencing visible negative consequences from the latter.

Another study [10] found that males exhibiting higher trait impulsivity and impulsive action tendencies in uncertain settings, along with stronger desire responses, showed significant symptoms of Internet Pornography-use Disorder (IPD). IPD refers to a specific type of Internet-use Disorder (IUD) characterized by a loss of control over consuming pornography online. This effect was observed only when individuals were exposed to pornographic content, not in a neutral context. The study involved fifty heterosexual male pornography consumers, with an average age of 23, who identified as heterosexual and enjoyed pornography depicting heterosexual intercourse. Participants were recruited through local ads at the University of Duisburg-Essen and online marketing within the university's internal networks.

3.2 The Collection of EEG Signal Data Related to Detecting Pornography Addiction

The initial phase in identifying pornography addiction through EEG-based BCI involves the recruitment and assembly of participants who meet the predefined criteria. Subsequently, data collection is initiated through experimental activities. Following this, the procedure includes generating an image of the EEG signal from the collected data, and then conducting the feature extraction process. Ultimately, the optimal classification method is determined.

The research in [11] involved the collection of a dataset using a 19-channel Brain Maker device, encompassing channels P4, O2, P8, T8, C4, Cz, Fz, F4, Fp2, F8, Fp1, F7, F3, C3, T7, P7, P3, O1, and Pz. Each participant performed nine activities in raw data, totaling 10 minutes, including tasks with eyes closed and open, expressing happiness, calmness, sadness, fear, engaging in memorization, an executive task, and a recall activity. Figures 1 and 2 illustrate the electrode placement map.

Two stimuli were employed in this experiment. The first stimulus involved inducing emotional states using images from the International Affective Picture System (IAPS) depicting happiness, calmness, sadness, and fear. Each emotion was represented by an image displayed for one minute. The second stimulus was an executive task featuring erotic visuals, and the images were provided by a psychologist. Both stimuli were utilized to observe the reactions of both porn addicts and non-porn addicts. The emotional state of participants during the executive task was inferred based on EEG signals obtained in multiple emotional states, following IAPS's standard procedure.

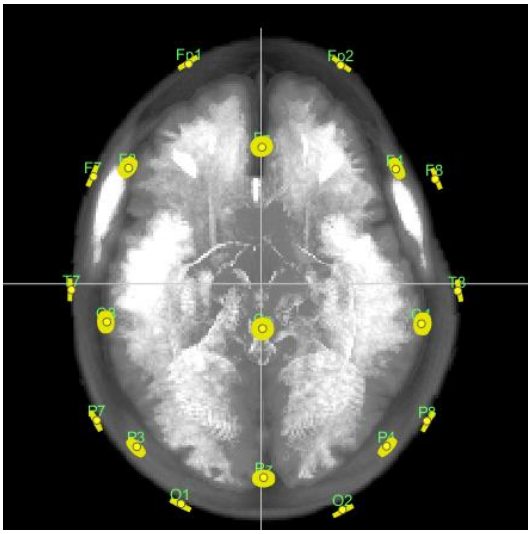

Fig. 1. The Placement of Electrodes (i)

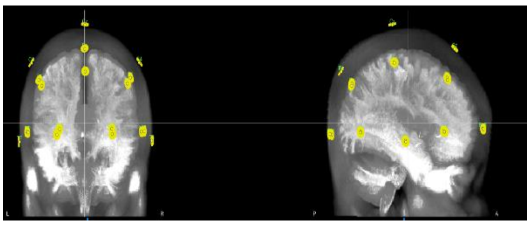

Fig. 2. The Placement of Electrodes (ii)

The examination of pornography addiction using MRI was undertaken by [12]. revealing a connection between pornographic materials and the ventral striatum. Nineteen men, averaging 25 years in age, were selected for the study. The Internet Addiction Test (sIAT) was employed to evaluate participants' cybersex addiction, assessing negative consequences such as loss of control, social problems, and mood regulation. Additional questionnaires, including the Sexual Excitation Scale (SES), Hypersexual Behavioural Inventory (HBI), and Brief Symptom Inventory (BSI), were administered. Participants were also tasked with evaluating 120 trial images using an MRI machine. The fMRI scanner utilized was a 7T whole-body research scanner (Magnetom 7T, Siemens Healthcare, Erlangen, Germany) with 32-channel signal generation and reception. Image data processing was performed using SPM8 (Statistical Parametric Mapping, Welcome Trust Centre for Neuroimaging, London). The MRI findings indicated that ventral striatum activity reflected the subjects' moment-by-moment sexual arousal in response to various pornographic images.

Analyzing EEG signals involves several steps, as demonstrated in research by [13] which proposed a method for EEG signal analysis encompassing preprocessing, feature extraction, and classification. Preprocessing aims to minimize data noise, feature extraction extracts useful information from the data, and classification, the final stage, predicts the data group.
In another study by [14], the discussion revolves around the Butterworth bandpass and stationary wavelet transform filters in the context of EEG signal analysis. The study compares the impact of these two filtering methods on EEG signals, utilizing mean square error (MSE) and peak-to-noise ratio (PSNR) as measures. The findings indicate that the stationary wavelet transform outperforms the Butterworth bandpass filter in all channels studied, with lower MSE values.

3.3 Methods Which Used to Analyze the EEG Signals in Relation to Detecting Pornography Addiction

Addictive behaviors are mirrored in brain activity. Magnetic resonance imaging, EEG, neuroendocrine, and cognitive studies could show that people with hypersexual or pornographic experiences have different brains [15]. Analyzing EEG signals involves several steps, as demonstrated in research by [13] which proposed a method for EEG signal analysis encompassing preprocessing, feature extraction, and classification. Preprocessing aims to minimize data noise, feature extraction extracts useful information from the data, and classification, the final stage, predicts the data group.

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EEG-based Brain-Computer Interface (BCI) has been utilized to explore various conditions, including the investigation of porn addiction in individuals with learning disabilities in a study by [16] The research involved 13 children from a clinic as participants, with 9 males and 5 females. EEG signals were measured with open and closed eyes using a 19-channel EEG device and BrainMarker. Subsequently, a psychological team conducted a questionnaire session. For data analysis, pre-processing and a bandpass filter were employed. Pre-processing aimed to eliminate noise data, and the bandpass filter targeted the removal of unwanted frequencies. Theta, alpha, and beta bands were selected for further investigation.

In another study, [3] employed a machine learning approach for detecting porn addiction, still intertwined with EEG data imagery. Researchers from the International Islamic University Malaysia (IIUM) gathered data from 14 Indonesian teenagers using an electroencephalogram (EEG) device. The dataset included EEG data from 14 participants, aged 9 to 13, although only data from 11 participants were utilized in the study. The dataset comprised 7 addicts and 4 non-addicts, with data collected for both closed and open eyes. For both eyes open and closed conditions, five band waves—alpha, theta, gamma, delta, and beta—were examined. Each band wave was subdivided into two basis functions based on Valence and Arousal data. Each participant contributed to 880 instances, and all data were in numerical values. The pre-processing of raw EEG data involved removing unwanted artifacts such as background noise and movement data. Subsequently, the Mel Frequency Cepstral Coefficient (MFCC) feature extraction method was applied to obtain relevant features. Three classification methods—Multi-Layer Perceptron, Naïve Bayes Classifier, and Random Forest—were utilized in their research.

Employing machine learning methods and utilizing EEG data, researchers [17] have also utilized a technique for identifying alcohol use disorder (AUD). The study comprised 30 individuals diagnosed with AUD, ranging in age from 12 to 55 years, and 15 healthy controls aged 16 to 43 years. These participants were recruited from the Bingkor clinic in Sabah, East Malaysia. In this investigation, experimental data comprised resting-state EEG recordings and clinical assessment scores. The EEG data were captured using the Discovery 24E EEG system, featuring 19 EEG channels positioned according to the international 10–20 system. The brain signals were digitized at a sampling rate of 256 samples per second. The EEG data underwent filtering within a frequency bandwidth of 0–70 Hz, with an additional 50 Hz notch filter applied to suppress line noises. Resting-state EEG data were recorded under two physiological conditions those are 5 minutes of eyes-closed (EC), and 5 minutes of eyes-open (EO). Resting-state EEG data exhibit a composite nature and are typically analyzed by decomposition into frequency bands such as delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–12 Hz), beta (12–30 Hz), and gamma (>30 Hz).

The following action involves noise reduction. To enhance the efficacy of noise removal, it is imperative that the chosen templates consist of a minimum of 60 seconds of artifact-free epochs extracted from the raw data. The reliability of the selected EEG segments was evaluated using the Split-Half reliability score (SHR score). The SHR score represents the ratio of variance between the odd and even time points of the time series derived from the selected EEG segments. The criteria for selection involved a SHR score exceeding 0.90. The proposed Machine Learning (ML) approach processed input data by dividing it into distinct training and testing sets using a 10-fold cross-validation to ensure their independence. Additionally, spectral powers and inter-hemispheric coherences were calculated from Resting EEG (REEG) data to investigate variations in these metrics between individuals with Alcohol Use Disorder (AUD) and control subjects. The computation of inter-hemispheric coherence involved pairwise comparisons between different EEG electrodes.

In this study [17], was involves the feature selection process to improve classification accuracy using a method based on feature weighting derived from ROC curves of individual features. Each feature's discriminative ability between target classes was reflected in the Area under the ROC curve (AUC), with values ranging from 0 to 0.5, indicating diverse classification abilities. Features were assigned weights and organized in descending order accordingly. Following the identification of the most discriminant features, classification was executed. These features were then used as input data for a logistic regression (LR) classifier, modeling the relationship between the reduced feature set and corresponding treatment outcomes (AUD patients and healthy controls). Among the EEG frequency bands, theta, delta, and high gamma bands demonstrated the highest classification performance, achieving an accuracy of 85%. Moreover, integrating all power bands resulted in an accuracy of 86.6%. Inter-hemispheric coherence exhibited an accuracy of 80.8%, which increased to 89.3% when combined with theta and high gamma features.

Regularized linear discriminant analysis (RLDA) classifier was conducted by [2] to classify motor imagery (MI) for ear with EEG based BCI . The research was used two datasets to evaluate the proposed methods. The first dataset involved the participation of five subjects in an experiment where MI tasks for the right hand, left hand, and foot were performed in a random order (50 times per class). The procedure consisted of displaying a blank screen for 0 to 3 seconds, followed by the appearance of a fixation cross at the center of the monitor for 3 to 6 seconds after a warning sound. Subsequently, a visual cue (right, left, down arrow) corresponding to each class was randomly assigned for 6 to 10 seconds. During the 4-second interval, subjects engaged in motor imagery. The entire experiment spanned approximately 30 minutes. EEG signals were recorded from 70 Ag/AgCl scalp electrodes using the international 10-20 system (Easy cap, BrainProduct), with reference to the nose tip and the AFz electrode serving as the ground. The data were sampled at 1,000 Hz. While the second dataset employed the BCI Competition III dataset IVa, featuring the participation of five healthy subjects in the experiment. EEG signals were recorded using 118 electrodes based on the 10-20 system and sampled at a rate of 250 Hz. Each subject conducted 140 trials for each MI task, respectively.

All EEG data underwent down-sampling to 100 Hz. Channel selection for classification involved around-the-ear channels (Dataset1: 14, Dataset2: 8) and motor area channels (Dataset1: 21, Dataset2: 21). A band-pass filter ranging from 8 Hz to 30 Hz was applied to the EEG data. For the FBCSP, nine band-pass filter banks were utilized (refer to [5] for detailed information). Time-delayed embedding varied from 1 to 15 in both the CSSP and the proposed method. OpenBMI, a Matlab-based open-source toolbox, was employed to process all EEG data.

In the classification of MI, optimizing the frequency band is a crucial consideration. To address this, we established the frequency band for time delay embedding signals using a spectral filter and 5-fold cross-validation. Initially, the lower bound of the frequency band was set based on the performance of the time delay embedding method [4]. Starting at 5 Hz, the lower bound was adjusted to a higher frequency if the current performance fell below that of the higher frequency. If not, the frequency was fixed as the lower bound of the frequency band. Conversely, the upper bound was determined in the opposite manner, commencing at 35 Hz since the 5 to 35 Hz frequency band encompasses both Mu (8-14 Hz) and Beta (14-30 Hz) rhythms, recognized as the most significant frequency bands for MI classification. A spatial filter was computed using common spatial patterns (CSP). Subsequently, log-variance features were classified using a regularized linear discriminant analysis (RLDA) classifier. The classification evaluation utilizing EEG signals from around the ear, the proposed method demonstrated accuracies of 71.80% and 68.07% for each respective dataset.

In other works, the neuro-fuzzy approach especially Fuzzy Relational NN (FRNN) for its classification properties to detect the resting state was introduced by [18]. The model-used is motivated by the recognition that the synergy between neural networks and fuzzy technology amplifies the capabilities of control, decision-making, and data analysis systems. The utilized data were acquired using a sampling rate of 128 Hz over a duration of 117 seconds. The bandwidth spans from 0.16 to 43 Hz, incorporating digital notch filters at 50 Hz and 60 Hz. The data collection involved labeling the eye state (0 for eye open and 1 for eye closed) across 14 electrode values (channels: AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4) for each temporal sample, aligned with the corresponding recorded video.

Noise reduction is employed in processing EEG signals to enhance signal quality and classification success. The prevailing methodologies largely rely on filtering techniques such as Wiener or Kalman filters, which prove effective when the spectral characteristics of both the signal without noise and the noise itself are well-understood. However, enhancements can be achieved by embracing adaptive filtering. In this scenario, noise reduction is directly applied to signals without requiring prior knowledge of their behavior and spectral properties, achieved through a learning methodology. In our study, noise reduction is accomplished through an adaptive approach employing a Neural Network (NN). Specifically, their approach involves the utilization of a single-layer feedforward Neural Network (NN) that relies on a Hebbian-type learning rule. This configuration is employed to achieve non-linear Principal Component Analysis (PCA). The process of noise reduction is achieved through the compression and subsequent decompression (reconstruction) of the raw data. This adaptive methodology relies on a robust generalization of variance maximization found in traditional Principal Component Analysis (PCA). Here, the objective function is presumed to be a valid cost function.

FRNN represents a neuro-fuzzy framework founded on fuzzy relational connections. The application of the FRNN model involves the utilization of two Gaussian membership functions for each channel, with Lukasiewicz t-norms for AND connectives and s-norms for OR connectives. The employment of the cross-validation mechanism, wherein the dataset is divided into training (75%), validation (15%), and test sets (15%) was conducted by [18]. The accuracy of flawless classification for all datasets hovers around 86%. Subsequently, the authors implement the described adaptive noise reduction approach for each individual channel.

4 Conclusions

The examination of the pornography issue is presented through the analysis of the review paper. This article comprehensively covers everything from the detrimental effects of pornography addiction to the methods employed for diagnosing it. The predominant approach for identifying pornography addiction is through EEG-based Brain-Computer Interface (BCI), involving various methods ranging from data processing and feature extraction to classification.

For a more accurate understanding, additional exploration of papers associated with the recognition of pornography addiction is essential. There is a need for more recent and targeted research specifically addressing the identification of pornographic addiction.

Acknowledgments. This study was initialized by Mr. Noor Akhmad Setiawan as the supervisor and supported by Mr. Ridi Ferdiana as the second supervisor.

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