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Neuro-Physiological porn addiction detection using machine learning approach

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ABSTRACT

Pornography is a portrayal of sexual subject contents for the exclusive purpose of sexual arousal that can lead to addiction. The Internet accessibility has created unprecedented opportunities for sexual education, learning, and growth. Hence, the risk of porn addiction developed by teenagers has also increased due to highly prevalent porn consumption. To date, the only available means of detecting porn addiction is through questionnaire. However, while answering the questions, participants may suppress or exaggerate their answers because porn addiction is considered taboo in the community. Hence, the purpose of this project is to develop an engine with multiple classifiers to recognize porn addiction using electroencephalography signals and to compare classifiers performance. In this work, three different classifiers of Multilayer Perceptron, Naive Bayesian, and Random Forest are employed. The experimental results show that the MLP classifier yielded slightly better accuracy compared to Naïve Bayes and Random Forest classifiers making the MLP classifier preferable for porn addiction recognition. Although this work is still at infancy stage, it is envisaged for the work to be expanded for comprehensive porn addiction recognition system so that early intervention and appropriate support can be given for the teenagers with pornography addiction problem.

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1. INTRODUCTION

Habit and addiction are the results of repeated activities being carried out for a long time. Although the two seems similar, habit can be controlled by the individuals while addiction is difficult to be controlled. Addiction can affect anybody and most people will eventually develop at least one of the habit into an addiction, which he/she often do it in their daily life [1]. People with an addiction have no longer any control on what they are doing, taking or use of the substance or behaviors that they are addicted to [2]. Addiction is simply referred to ‘giving over’ or being ‘highly devoted’ to a person or activity, or engaging in a behavior habitually which could have positive or negative implications [3]. Addiction can be divided into 2 types, namely; behaviour and substance addictions respectively [4]. According to [5], substance addiction is a neuropsychiatric disorder and can be characterized by a recurring desire to continue taking the substance despite harmful consequences in which it could be drugs, alcohol, sex and gambling. The most common substance is drug addiction where the addicts have not only abuse one type of drug but may combine multiple types of drugs or trying different type of drugs [6]. The non-substance addiction (behavioural addiction) covers activities such as pathological gambling, food addiction, internet addiction and mobile phone addiction. Hence, pornography addiction can be classified as one of the behavioural addictions.

Pornography is the portrayal of sexual subject matter for the exclusive purpose of sexual arousal [7]. Porn addiction is an addiction model of compulsive sexual activity with concurrent use of pornographic materials, despite negative consequences to an individual physical, mental, social, or financial well-being [8]. There are many sources that allow porn addicts to access pornography and sexual amusement with several media accessibility such as sexual pictures, audios, videos and written materials. The pornography materials can be sourced through electronic media (television, radio and DVDs), print media (newspaper and magazine) and the internet [9]. At present, 25% of the total daily search engine demands are for pornography contents with 68 million pornographic demands in the searching [10] requested from 4.2 million pornographic websites with the average age of first internet pornography exposure is 11 years old.

The intense use of pornography is strongly related to sexual aggression which the content of the pornography can lead to a violent crime [11]. The cause of such addiction might be harmful not only for the individual but also affecting the society such as the rape cases and inappropriate behaviour. According to [12], the factor of genes and age itself might lead the addicts for having a stronger addiction towards something. Environmental factor may also added to the factor that influence an individual addiction.

This project focuses on the alternative measurement of porn addiction for teenagers to detect whether they may have porn addiction or not based on their brain responses during the initial stage at eyes open and eyes close. These EEG signals during the initial stage will provide enough information to the biasness of the frontal part of the brain responses. This is to offer a psychological approach that may give better measurement to detect porn addiction among teenagers.

2. LITERATURE REVIEW

Electroencephalography (EEG) is made of electrodes and it measures the brain activities from the scalp. Brain has 100 billion neurons and the information are passed from one neuron to the other through the firing of the neurons. The electrodes in EEG measure changes in the electrical potential of the neurons. Figure 1 shows the international 10-20 system of electrode placement that are commonly used when analysing brain waves. It broadly described the location of electrodes at the unique intervals alongside the head. Every electrode node has a letter to discover the lobe, along with valuable number or another letter to perceive the hemispheric region of either the right and left side of the scalp [13]. The electrodes are placed at specific distance from each other. The odd numbers are recording activity from the left side and the even numbers are recording activity from the right side. For the centre or middle line, it is denoted as Z. Fp means frontal polar and F3 also is a frontal polar electrode. C3 it is in the central location which is located at the centre line. Meanwhile, P3 is recording from the parietal region and lastly, O is recording the occipital region.

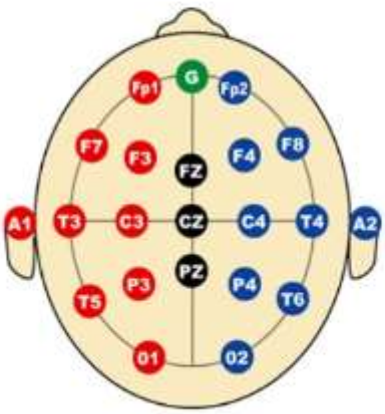
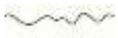
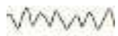
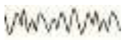
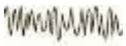


Figure 1. The international 10-20 electrode placement system

Although the brainwave signals are low frequencies (between 0.1hz to 50 hz), they are normally catergorized into five bands of delta, theta, apla, beta and gamma as described in Table 1. Interestingly each band indicate certain functionality of the brains and normally indicate an activation of the part of the brain close to the scalp region.

Table 1. The Brain Wave Frequencies Categories

Categories (Wave type)	Waves	Frequency (Hz)	Functions
Delta		0.1 – 3	Instinct: Survival, Deep Sleep, Coma, Dreaming
Theta		4 – 7	Emotion: Feelings, Dreams, Drowsy, Idea-ling
Alpha		8 – 12	Consciousness: Awareness of body, Integration of Feelings, Relax
Beta		13 – 40	Concentration: Thinking, Perception, Mental Activity, Alert
uGamma		40 – 44	Spiritual: Cognitive Decline, Short-Term Memory, Quiet, Consciousness

Psychological findings on detecting porn addiction involves questionaire [14] for adults while for kids, the parents and teachers will be involved with the questionaire. Such scenario can pose as a challenge especially if parents have the tendency to suppress their children situation [15]. There has been studies to analyse porn addiction using the brain wave patterns [16, 17]. However, such study only considers the power distribution of the frontal areas during the eyes open and eyes close and comparison with learning disabilities [18]. In this project we look into other artifitial intelligence (AI) tools using machine learning to analyse the brain wave pattern at eyes open and eyes close and this is the initial condition of the brain.

3. RESULTS AND DISCUSSION

Figure 2 shows the flow of the project that consists of data collections, feature extractions and classifications. In this project, we only focus on the classifications using AI techniques to understand the robustness of the classifications based on three classifiers namely the Multi Layer Perceptron (MLP), Naive Bayesian (NB) and Random Forest (RF).

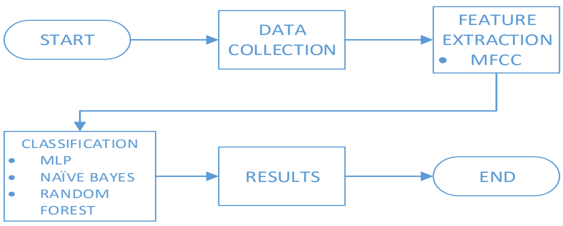


Figure 2. The proposed system flow chart

3.1. Data Collection

The data collection was prepared by the International Islamic University Malaysia (IIUM) researchers using the electroencephalogram (EEG) device for 14 Indonesian teenagers [17]. There are a total of 14 participants with age ranging between 9 to 13 years old EEG data was collected but only 11 participants data were used in this study. The EEG data received in a form of spreadsheet excel file and the participants addiction status are already labelled based on the psychological questionnaire answers. The EEG raw data are pre-processed to remove unwanted artefacts such as background noise and movement data. Then, the Mel Frequency Cepstral Coefficient (MFCC) feature extraction method is applied to get the relevant features. The MFCC features are widely used in extracting relevant features in speech that approximates the human auditory system. It had been used in previous studies [17, 18] and the experimental results show potential of using such feature extraction method to extract relevant features from brain signals.

The data consists of 7 addicts and 4 non-addicts and for each participant has eyes close and eyes open data. There are 5 band waves for the eyes open and eyes close data, namely; alpha, theta, gamma, delta and beta. Each band wave have been divided into 2 basis function of Valence and Arousal data. There are 880 instances involve for a participant and all of the data received is in numerical values.

3.2. Multi-layer Perceptron

For simplicity, only two and three layer multi-layer perceptron (MLP) were used with the same number of neurons. Starting from 50 neurons, the number of tested neurons was increased to 72, 100, 250 neurons, as there are features in our data set along with 1000 max iterations. Once the model is created, the training data is fitted to the model [19, 20]. Each instances of the data will be used to train the network for porn addicts or otherwise.

3.3. Naïve Bayes

The dataset contains 3 classes of 880 instances each, where each class refers to a type label. The GaussianNB and BernoulliNB models are available in the Sckit-learn Library [21]. Gaussian Naïve Bayes is used in cases when all of the features are continuous. Meanwhile, Bernoulli Naïve Bayes assumes that all features are binary such that it takes only two values such as 0 to represents as non-addicts and 1 to represents as addicts. The feature class needs a label, which is denoted as the “label” class. If the feature values are numerical, "bin" is needed to reduce the number of possible feature values. The first row does not need to “bin” because it is a class row, so bin_width will be set to None. Two features will be created where one feature class contains the label for the Naive Bayes class ‘Valence’ and one the label for the class ‘Arousal’.

3.4. Random Forest

Deep trees were constructed with a minimum number of training rows at each node of 1. Samples of the training dataset were created with the same size as the original dataset, which is a default expectation for the Random Forest algorithm [22]. The number of features considered at each split point was set into ‘auto’, ‘sqrt’ and ‘log2’. A suite of 3 different numbers of trees were evaluated for comparison, showing the increasing skill as more trees are added. This parameter defines the number of trees in the random forest. It will start with n_estimator = 1000 to see how the algorithm performs.

3.5. K-fold Validation

All classification models inside the present work had been trained and tested with EEG data after which it is confirmed using k-fold cross validation. K-fold cross validation is a technique that commonly used to compare the performance between two classifiers and to evaluates a classifier’s performance from the extracted data [23]. It has the benefit of the use of all instances in an extracted data for either training or testing, wherein every instance is employed for validation exactly once. For this project, only testing phase will be done. The two phases represent the K-fold cross validation.

For this project, there will be 5-fold cross validation that each dataset consists of 80:20 testing. The k-fold cross validation will be divided into k subsets which (k-1) subset is used for training phases and one remaining subset for testing phases. To test all the classifiers, k times of each subset process is repeated. Classifier performance was measure for their accuracy as follows:

$$\text{Accuracy} = \frac{\text{Total no.of correctly classified instances}}{\text{Total numbers of instances}} \text{ x } 100$$

4. PRELIMANARY EXPERIMENT

This section focused on the data mining experience using Python and Weka as tools that are widely used in field of data analytics [24].

Table 2. MLP Accuracy Comparison between WEKA and Python for Subject1

Wave	Eyes Open			Eyes Close		
Frequencies	WEKA (%)	Python (%)	Difference	WEKA (%)	Python (%)	Difference
Alpha	71	76	+5	82	82	-
Beta	61	65	+4	69	69	-
Delta	74	74	-	70	73	+3
Gamma	70	70	-	65	66	+1
Theta	68	70	+2	74	74	-

The experiments were performed using a tool named Weka 3.8.3. Weka 3.8.3 is a tool where pre-processing data can be made. Weka is a built-in feature that require no programming and coding knowledge. Classification also can be conducted using this tool. The results of Weka will be compared with Anaconda 2.7 (for Python). For start-up experiments, sets of CSV data is loaded in WEKA and percentage split was set to 80%. The Multi-Layer Perceptron classifier is selected for accuracy comparison between WEKA and Python. The comparison results of WEKA and Python is presented in Table 2. In both cases, the results are very close with maximum difference of 5% for experiment using Python in Alpha wave frequencies for eyes open. It is also observed that Python score slightly better accuracy in eyes close experiment with 3% better performance using delta waves. Hence, Python implementation will be used for the further analysis since Python managed to yield better performance.

5. RESULTS AND DISCUSSION

In this section will show the performance of the three different classifiers based on Python as the tools. The results are analysed and compared to see the performance of each machine learning classifiers. From the previous studies on analysing the EEG data, only the resting state of eye open and eye close data are used because it is sufficient to provide the initial screening of the subjects [25, 26].

5.1. Multi-layer Perceptron Accuracy Result

For Multi-Layer Perceptron (MLP), the experiments were focused on determining the optimal parameters which have the same number of learning epochs but different number of hidden layers and the time computational taken. Tables 3 shows the results of using alpha and gamma waves respectively for eyes open and eyes close experiments.

Table 3. MLP Experimental Results

MLP Number of Neurons	Alpha Wave				Gamma Wave			
	Eyes Open		Eyes close		Eyes Open		Eyes close	
	Acc (%)	CT (S)	Acc (%)	CT (S)	Acc (%)	CT (S)	Acc (%)	CT (S)
50,50	88	78.11	89	58.25	67	30.63	55	36.73
72,72	88	86.35	88	53.19	67	41.55	56	37.03
100,100	88	86.10	89	62.25	66	47.92	56	40.26
250,250	88	188.79	88	140.68	70	113.94	57	104.47
50,50,50	88	64.38	88	89.57	68	34.51	56	32.76
72,72,72	88	69.08	89	53.58	69	43.39	57	34.12
100,100,100	88	81.91	89	64.06	71	49.93	57	48.53
250,250,250	88	236.36	88	191.64	70	162.12	58	137.93

* ACC= Accuracy, CT = Computation Time

From the observations, it clearly show that Alpha waves yielded highest accuracy compared to all the band waves and Gamma has the lowest. Almost all results seems to be consistent with accuracy ranging from 88% to 89% for both eyes open or eyes close conditions. It is interesting to note that as the number of neurons increases, the compution will also increase resulting in higher computation time. Thus, a two-layer MLP is sufficient to produce a reasonably consistant good results and requires less than 80s of computation time.

5.2. Naïve Bayes Accuracy Result

For Naïve Bayes, the experiments were focused on determining the optimal parameters which have the same number of learning epochs but different model of Naïve Bayes. Gaussian and Bernoulli Naïve Bayes are used for this experimental study. Table 4 shows the results of the Gaussian Naïve Bayes and Bernoulli Naïve Bayes for eyes open and eyes close conditions respectively.

Table 4. Naïve Bayes Experimental Result

Band	Gaussian Naïve Bayes				Bernoulli Naïve Bayes			
	Eyes Open		Eyes close		Eyes Open		Eyes close	
	Acc (%)	CT (S)	Acc (%)	CT (S)	Acc (%)	CT (S)	Acc (%)	CT (S)
Alpha	84	5.16	86	6.37	82	4.40	84	4.63
Beta	77	5.73	74	6.37	75	4.39	72	6.53
Delta	68	5.92	58	6.61	62	6.25	55	3.68
Gamma	64	7.50	57	6.93	64	4.24	55	3.66
Theta	62	8.72	66	16.40	62	4.48	64	3.74

* ACC= Accuracy, CT = Computation Time

In both cases the result of the eyes open or eyes close for alpha waves seems to produces the best performance. This is consistent with the previous results using MLP. Computation time for all cases seems to be below 10s except for theta waves for eyes close condition. Moreover, the results for Bernoulli Naïve Bayes is also consistent with the best accuracy is recorded using alpha waves with accuracy greater than 80%

and computation time is less than 7 seconds. When comparing both types of Bernoulli and Gaussian Naïve Bayes classifier, it is observed that Gaussian Naïve Bayes give higher accuracy than Bernoulli Naïve Bayes in eyes close condition. Hence, from this observation, Gaussian Naïve Bayes model is more favourable than Bernoulli Naïve Bayes classifier.

5.3. Random Forest Accuracy Result

The experiments using Random Forest as the classifiers were also conducted. The parameters that had been varied for the experiments was the number of trees in the forest. All other parameters were set to the standard values offered by the model. The numbers of trees were varied to 10 and the parameter for maximum features was tested with different features. Table 5, 6 and 7 show the results of using auto, sqrt root and log2 settings respectively for eyes open and eyes close conditions for different waves. It can be seen that alpha waves still produce the best performance of above 80% for both eyes open and close conditions in all settings. It is also noted that Random Forest classifier requires longer computation time that is greater than 200s as compared to Naïve Bayes and MLP classifiers.

Table 5. Random Forest ‘Auto’ Setting Result for Eyes Open and Eyes Close

Band	Eyes Open		Eyes close	
	Accuracy (%)	Computation Time (S)	Accuracy (%)	Computation Time (S)
Alpha	82	231.47	82	263.78
Beta	67	274.05	69	274.84
Delta	73	291.11	69	262.10
Gamma	64	259.61	52	262.43
Theta	65	270.59	68	228.28

Table 6. Random Forest ‘Sqrt’ Setting Result for Eyes Open and Eyes Close

Band	Eyes Open		Eyes close	
	Accuracy (%)	Computation Time (S)	Accuracy (%)	Computation Time (S)
Alpha	82	215.36	82	215.30
Beta	69	242.93	69	248.43
Delta	73	217.99	69	234.41
Gamma	64	231.95	52	245.10
Theta	65	229.69	68	240.17

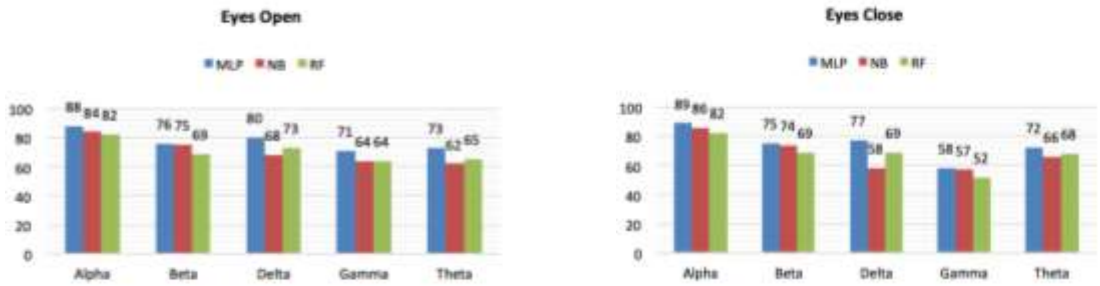
Table 7. Random Forest ‘log2’ Setting Result for Eyes Open and Eyes Close

Band	Eyes Open		Eyes close	
	Accuracy (%)	Computation Time (S)	Accuracy (%)	Computation Time (S)
Alpha	82	226.75	82	214.32
Beta	69	244.32	69	244.21
Delta	73	218.06	69	227.36
Gamma	64	232.33	52	243.03
Theta	65	242.28	68	226.19

5.4. Discussion

After the results of all the experiments for each classifier were obtained, final analysis and evaluation were conducted. The analysis was recorded and comparison graphs for each classifier and representation of data were presented. Finally, the results were summarized in Figure 3.

It was clear that Multi-Layer Perceptron gave higher accuracy results than Naïve Bayes and Random Forest for eyes open and eyes close conditions. The Multi-Layer Perceptron classifier contributed a lot of training process using the model due to the high number of layers and neurons. The discovery is based on the observation that the higher the parameters of layers and neurons, the better the prediction performance. In all cases alpha waves yielded the best predicted accuracy as compared to all subjects in both conditions. Naives Bayes gives the shortest computation time with Gaussian Naives Bayes classifier performs better than Bernoulli Naives Bayes classifier. Figure 3 also shows a clear result that Multi-Layer Perceptron classifier gave more accurate prediction results. The peak accuracy result was produced from Alpha and the lowest accuracy results was produced from Gamma. It is also noted that a big difference of accuracy occurs between Multi-Layer Perceptron and Naïve Bayes in Delta brain waves.



(a) (b)

Figure 3. Performance comparison of (a) eyes open and (b) eyes close conditions

6. CONCLUSION

From the results and observation it is clear that alpha waves can be used to detect porn addiction effectively especially within the frontal region of the brain. The valence and arousal were used in this case and seems to provide robust prediction of porn addiction preliminary screening. The results is also based on the fact that the questionaire produce by the psychologist is accurate enough and from [14] it is found the other 20% of the accuracy could be due to inconsistency of the psychological instruments used. For efficient computation time, the Naïve Bayes classifier can produce the fastest with reasonably good enough accuracy. However, MLP outperformed both Naives Bayes and Random Forest classifiers in term of accuracy. The experimental results show potential for expension for porn addiction detection that it can be used for early intervention and alternative measurement to support psychological questionnaire methods [27].

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