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A Game Player Expertise Level Classification System Using Electroencephalography (EEG)

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Abstract: The success and wider adaptability of smart phones has given a new dimension to the gaming industry. Due to the wide spectrum of video games, the success of a particular game depends on how efficiently it is able to capture the end users' attention. This leads to the need to analyse the cognitive aspects of the end user, that is the game player, during game play. A direct window to see how an end user responds to a stimuli is to look at their brain activity. In this study, electroencephalography (EEG) is used to record human brain activity during game play. A commercially available EEG headset is used for this purpose giving fourteen channels of recorded EEG brain activity. The aim is to classify a player as expert or novice using the brain activity as the player indulges in the game play. Three different machine learning classifiers have been used to train and test the system. Among the classifiers, naive Bayes has outperformed others with an accuracy of 88%, when data from all fourteen EEG channels are used. Furthermore, the activity observed on electrodes is statistically analysed and mapped for brain visualizations. The analysis has shown that out of the available fourteen channels, only four channels in the frontal and occipital brain regions show significant activity. Features of these four channels are then used, and the performance parameters of the four-channel classification are compared to the results of the fourteen-channel classification. It has been observed that support vector machine and the naive Bayes give good classification accuracy and processing time, well suited for real-time applications.

Keywords: electroencephalography (EEG); machine learning; consumer gaming; feature extraction; classification

1. Introduction

The video game industry is one of the major industries that incorporates many sub-disciplines. The target audience of this industry has grown from a more narrow clientele base to the main stream in recent years. The biggest catalyst has been the availability and accessibility of computer systems. Gaming has been a major part of the entertainment industry and is now becoming a way of life in learning, task management and simulation activities. A positive effect is seen on the gaming industry with an advancement in computing capabilities. The user experience with games is improved by the advanced computing graphics due to the availability of more computing power. At the same time, the game industry is going through a transformation due to a wider availability of smart phones and tablet devices. Games for smart devices now compete with classical console- and computer-based games and have attracted the attention of people from all walks of life. This renewed interest is mostly seen in mobile- and handheld device-based games as compared to console games [1]. The focus of recent development in the gaming industry covers both entertainment and educational purposes [2].

In the last few years, different methods have been proposed to assess the cognitive aspect of human response to video games [3,4]. For instance, electroencephalography (EEG) has been employed to analyse stress in computer game players [5]. Physiological signals are employed to analyse the learning outcome of digital games [6]. It has also been observed that video game training enhances cognitive control in older adults [7]. EEG-based experiments have been conducted in healthy, as well as diseased persons [8]. A neuro-feedback game has been used to enhance the attention in players [9]. EEG has also been used to enhance the game play experience of players [10]. The classification of the expertise level of a mobile game player during earlier stages of the game play can be fed back to the user. This would further entice players' interest in the game and allow assessing the cognitive aspects, as well.

Brain computer interfaces (BCIs) have already been used in game development [11]. Automated controls within the game play that come from human brain signals can be the next big thing in the gaming industry. This would also increase the spectrum of game users to those people who have some physical impairment and are not able to perform game controls by physical movements. The time and money spent on mobile games has increased considerably. This fact becomes obvious by looking at the application download patterns on various mobile-based platforms [12]. This directly translates into a massive increase in the number of mobile game players, and hence, their analysis and cognitive assessment have gained significant importance. In [13], an analysis of the mobile game players' experience was performed based on different BCI controls. Electrophysiological measurements have been used to examine the players' response to games [14,15]. EEG has also been used to measure the cognitive state of the brain such as stress [16]. In [17], field experts discussed the methodological advancements within player experience and playability research considering EEG as a good measure for cognitive processing. In [18], several methods were proposed to extract useful information from the observed human EEG activities. These methods involve three common operational steps. In the first step, data are preprocessed for noise reduction. Secondly, useful features are extracted from the preprocessed data. In the third step, classification is performed using the extracted features. The motivational states have been predicted based on brain activity for game play [19]. A non-EEG-based method to classify expert and novice levels of a game player is presented in [20], where objective-based action sequences are used. However, the approach only measures how certain objectives are achieved during game play for classification, which is a subjective measure. In [21], an analysis of the experience of a video game player is presented based on recorded EEG signals and shows that wearable EEG devices can be used for game analytics and to differentiate various cognitive processes.

In summary, there are various EEG-based methods presented in literature for game analytics and the evaluation of human response, as well as non-EEG-based methods for the classification of video game player expertise level. To the best of our knowledge, the same task has not been achieved using EEG and is presented in this study by using a method that classifies the expertise level of a game player into two classes, i.e., expert and novice. The aim is to explore whether, EEG can be used to tell how good a player is in a video game just by looking at the brain activity recorded during the game play and how certain brain areas play a more significant role than others. Game analytics and the human psychological response comprise a very interesting field of research as seen from the literature and the increasing use of mobile games in different fields of life. Video game play holds exciting promise as an activity that may provide generalized enhancement to a wide range of perceptual and cognitive abilities. Looking at these patterns, this study is conducted with a wider perspective of advancing research applications in psychology, BCI and the human cognition process. The study expands on the pilot study in [22] where initial data were recorded and the hypothesis of predicting the expertise of a game player was tested. In this study, data have been collected more rigorously to avoid artefacts and gender bias by adding more data to the experimental design. After noise reduction, features are extracted in the time domain from fourteen, as well as four selected EEG channels showing significant brain activity. Multiple classification algorithms are used to predict the expert-novice level of the player, and the results are evaluated using multiple performance metrics. The major contributions of this study are,

1. EEG-based data are recorded from multiple participants during the play of a mobile game to automatically classify the player as expert or novice on the basis of brain activity.
2. Those significant brain areas are highlighted and selected as being affected during the game play after a careful statistical analysis.
3. Thirteen morphological features are extracted in the time domain for classification purposes.

In Section 2, the proposed methodology and experimental setup to classify the players' expertise level are provided. Experimental results are presented and discussed in Section 3, followed by the conclusion and future work in Section 4.

2. Proposed Methodology

The steps involved in analysing the brain signals recorded using wearable EEG for the expert-novice classification of a game player are shown in Figure 1. The detail of each step is as follows.

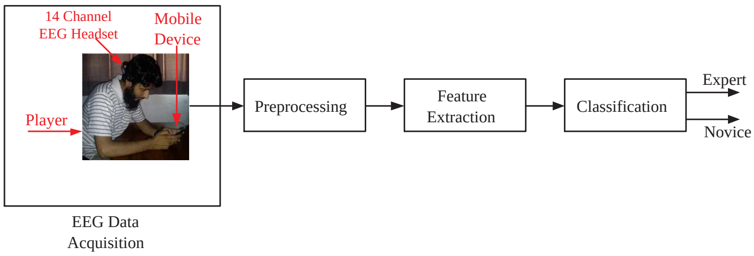


Figure 1. Block diagram of various processing steps used in this study for the purpose of expert-novice classification of game players on a consumer gaming machine using electroencephalography (EEG).

2.1. EEG Data Acquisition

The electrical activity of the brain is recorded using EEG by electrodes placed on the human scalp. The recorded brain activity is represented as waves with varying frequencies and amplitudes. The frequency variation of the signal is measured in hertz (Hz), whereas the amplitude variation is in the micro-volt range and represents the electrical activity of the brain. The frequency behaviour of the EEG signals is generally classified into five different bands i.e., alpha, beta, theta, gamma and delta, where each band could signify different physiological states of mind. A particular state of mind can be activated by using different stimuli such as audio and video [23]. The details of stimuli, participants and procedures used in this study are presented as follows.

2.1.1. Stimuli

In most EEG-based studies, a stimulus is required to activate the desired response. The game named *TempleRun*is selected as a stimulus for this study. The game has been widely downloaded and played and is selected due to its popularity among smart phone and tablet device users. Temple Run is a never-ending game developed by IMANGI studios http://imangistudios.com/. In this game, a character that runs in the temple after stealing the treasure is controlled by the mobile game player. The character is followed by "demonic monkeys" that can eat the character. The game ends in the case of character death either by falling from the temple or being eaten by the monkey. The player can manoeuvre the character in left and right directions, jump and slide to avoid obstacles. The direction of the character can also be controlled by tilting the smart phone and hand-held devices.

2.1.2. Participants

The EEG data are recorded using a wearable device for 20 healthy subjects including 70% male and 30% female participants. The age of these participants ranged between 18 and 23 years, with a mean age of 20.33 years. The participants are selected from a relatively younger age group, since this age group is most likely to engage in mobile game play. All participants belonged to the Asian Pacific ethnicity, having a similar educational background with no self-reported mental illness. The participants involved in this experiment used to play mobile games with an average frequency of four days per week. This frequency of game play is self-reported by the participants and is recorded to analyse the expertise level. Informed consent was taken from all participants for using the recorded brain signals for the purpose of this research.

2.1.3. Apparatus

The raw EEG data are recorded using a commercially-available EMOTIV (San Francisco, CA, USA) EPOC EEG headset with the EMOTIV Premium SDK software development kit (SDK) v 3.3.3, San Francisco, CA, USA. The observed data are stored in the European data format (EDF). The headset provides fourteen micro-electrodes for recording EEG activity including F3, F4, F7, F8, AF3, AF4, P7, P8, T7, T8, FC5, FC6, O1 and O2. The even- and odd-numbered channels represent electrodes for the right and left hemispheres of the brain, respectively. In addition to the fourteen channels, there are two additional electrodes that act as the reference for each hemisphere of the head. Saline liquid is used to hydrate the electrodes to reduce the resistance of connection between electrode and skull. Figure 2 shows the reference location of electrodes on the player's scalp providing coverage in the frontal, temporal, parietal and occipital regions of the brain. The spatial placement of electrodes of the EMOTIV EPOCH EEG fourteen-channel headset follows the international 10–20electrode positioning system [24]. The exact location of these channels can vary depending on the head size and hair length of participants. The EMOTIV headset is made flexible to adjust to all head sizes. The recorded brain waves represent the activity in a local brain region, and with the sparse placement of electrodes, it is not effected by slight displacement in location. The recorded data are transmitted over a wireless Bluetooth interface using a proprietary dongle that is connected through a USB connection to a computer system running the EMOTIV SDK.

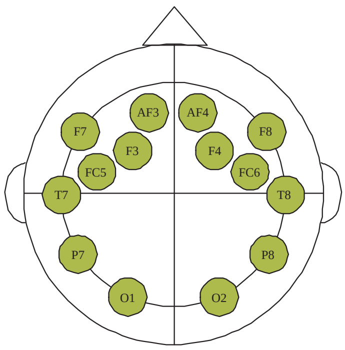


Figure 2. The 10–20 electrode positioning supported by EMOTIV [24].

2.1.4. Procedure

The data were recorded in a room where participants were provided with a comfortable environment and a smart phone for game play. The sources of environmental noise were kept to a minimum by avoiding electric cabling near the setup. The wireless headset and the SDK were properly synchronised to avoid any error in EEG signal acquisition during the game play. The sequence of steps, including the setup, game play and rest durations, is shown in Figure 3. Each participant was given a briefing on the sequence of steps, and the device was properly placed on the participant's head.

For each individual, five turns of playing temple run were used for the purpose of data recording separated by a rest time of one minute. The time for each turn varied for each participant and was represented by T1, T2, T3, T4 and T5. The average time taken to record the complete data for five turns for a single participant was 14.3 minutes with a total of 286 minutes of EEG recording used in this study. Since the expertise level cannot be reliably judged with a single turn, to be more rational, five turns were used.The number of turns was selected after careful experimentation, where the average scores were able to differentiate between an expert and novice player in the training set. For supervised learning, each player was assigned a novice or expert label based on a threshold, Z, calculated by adding and averaging the scores as,

$$Z = \frac{1}{U \times R} \sum_{i}^{U} \sum_{j}^{R} Score(i, j), \tag{1}$$

where U is the number of users, R is the number of turns and $Score(i, j)$ is the score for the j-th turn by the i-th player. The assigned labels corresponded to the self-reported expertise level of players. Participant average scores and the threshold value are shown in Figure 4. This resulted in 8 players classified as expert and 12 players classified as novice and are shown by blue and orange bars, respectively. The time taken by each participant in all turns is presented in Table 1, where $T1$, $T2$, $T3$, $T4$ and $T5$ represent the time for five turns, and $R1$, $R2$, $R3$ and $R4$ represent the rest time. The rest time between each turn is 60 seconds.

Table 1. The time taken for different turns by all users involved in the study (times for $T1$, $T2$, $T3$, $T4$, $T5$, $R1$, $R2$, $R3$ and $R4$ are in minutes).

Player	*T1*	*R1*	*T2*	*R2*	*T3*	*R3*	*T4*	*R4*	*T5*	Total Time (Minutes)
1	0.70	1	0.90	1	0.60	1	0.50	1	1.30	8
2	1.60	1	1.80	1	2.20	1	2.05	1	2.42	14.07
3	7.60	1	5.40	1	6.00	1	5.95	1	6.80	35.75
4	1.20	1	1.40	1	1.20	1	1.70	1	1.80	11.30
5	2.45	1	2.68	1	2.20	1	2.90	1	2.10	16.33
6	0.84	1	0.64	1	0.76	1	0.90	1	0.54	7.68
7	2.60	1	3.30	1	1.10	1	2.47	1	2.33	15.83
8	0.61	1	0.72	1	0.90	1	0.40	1	0.80	7.44
9	0.95	1	0.89	1	0.84	1	0.87	1	0.80	8.35
10	0.50	1	0.70	1	0.70	1	0.80	1	0.30	7.00
11	7.30	1	6.70	1	3.20	1	8.10	1	7.70	37.00
12	0.40	1	0.80	1	0.60	1	0.25	1	1.10	7.15
13	0.25	1	0.45	1	0.70	1	0.40	1	0.80	6.60
14	2.10	1	0.60	1	1.50	1	1.02	1	0.90	10.12
15	3.20	1	2.20	1	1.50	1	2.65	1	2.10	15.65
16	0.80	1	0.70	1	0.50	1	0.40	1	1.20	7.60
17	6.40	1	3.00	1	6.80	1	5.20	1	5.90	31.30
18	0.50	1	0.60	1	0.80	1	0.90	1	0.65	7.45
19	0.30	1	0.45	1	0.60	1	0.45	1	0.89	6.69
20	3.30	1	2.40	1	5.80	1	4.80	1	4.40	24.70

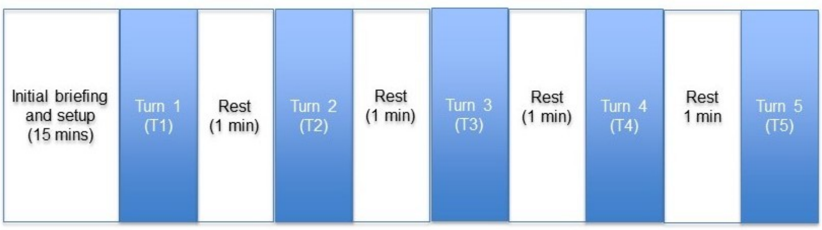


Figure 3. The experimental procedure used to record the data of game players.

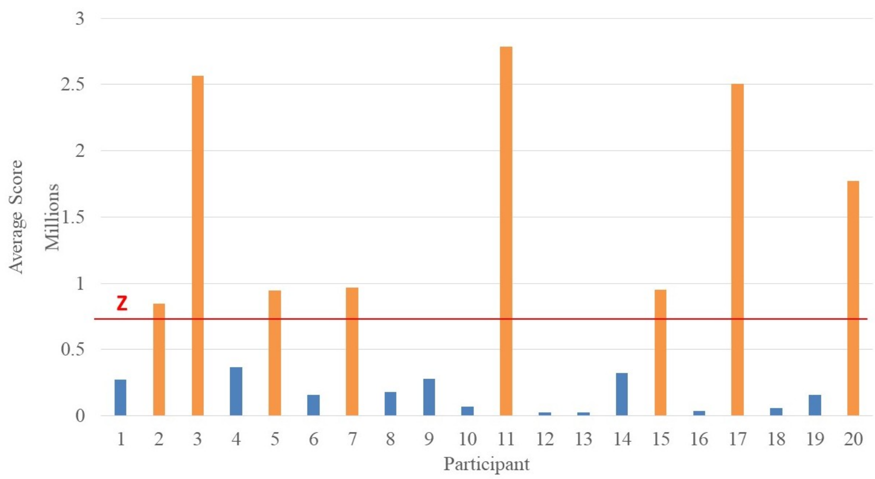


Figure 4. The average score of players and the threshold value for the players as novice or expert. The horizontal solid line shows the threshold value calculated using Equation (1).

2.2. Preprocessing

The EEG data recorded by the wireless EMOTIV headset are affected by different kinds of artefacts and need to be preprocessed to improve the quality of signals. These artefacts include noise from electrical lines, muscle movement, heart beat, sweating, electrode movement, and so on. The EEG signals have a bandwidth between 0.2 and 100 Hz and are recorded with 128 samples per second. In order to remove the DC offset, the mean value is subtracted from the entire data. For noise removal, a two-step process is applied including filtering and independent component analysis (ICA). The artefacts caused by physical movements such as heart beat and eye blink appear in the frequency range between 1.2 Hz and 5 Hz. The muscular movements effect the EEG oscillations above 45 Hz. The high gamma band is shown to have the highest correlation with motor-evoked potentials (MEPs) [25]. A first-order band-pass Butterworth filter with a pass-band of 5–45 Hz is used to remove artefacts caused by biological movements. The filtering process removes part of the delta and gamma waves, but the experimental procedure does not include any audio source. The selected game for this study does not rely on memory, as the game play is random for each turn. The filtering process is also useful in removing the power interference that occurs at 50 Hz. The proposed method also finds the significant channels that can be used for classification of player expertise level. It is a known fact that EEG recordings from multiple channels represent information that is a mixture of underlying sources from different brain areas. Hence, ICA is used to estimate independent sources from highly correlated EEG data [26]. ICA is a blind source separation technique, which statistically separates uncorrelated signals. ICA is performed using EEG lab [27] on the raw EEG data, and the separate components are used for feature extraction.

2.3. Feature Extraction

The important information contained in the data can be retained using features that are significant and uncorrelated. In the feature extraction stage, thirteen morphological features in the time domain are extracted from all the recorded EEG data. The features represent the underlying structure of the EEG signal that is expected to vary with the expertise level of game players. The mathematical details of the features are as follows and are reported in [28].

1. Maximum value (s_{max}):
$$s_{max} = \max\{s(t)\}. \tag{2}$$
2. Maximum value time ($t_{s_{max}}$):
$$t_{s_{max}} = \{t | s(t) = s_{max}\}, \tag{3}$$

where s_{max} is the signal maximum value.

3. Minimum value (s_{min}):

$$s_{min} = \min\{s(t)\}. \tag{4}$$

4. Minimum value time ($t_{s_{min}}$):

$$t_{s_{min}} = \{t|s(t) = s_{min}\}, \tag{5}$$

where s_{min} is the signal minimum value.

5. Maximum absolute value (MAV):

$$MAV = |s_{max}|. \tag{6}$$

6. Peak to peak signal value (s_{pp}):

$$s_{pp} = s_{max} - s_{min}. \tag{7}$$

7. Latency to maximum value ratio (L_{max}):

$$L_{max} = \frac{t_{s_{max}}}{s_{max}}. \tag{8}$$

8. Latency to minimum value ratio (L_{min}):

$$L_{min} = \frac{t_{s_{min}}}{s_{min}}. \tag{9}$$

9. Peak to peak time window (t_{pp}):

$$t_{pp} = t_{s_{max}} + t_{s_{min}}. \tag{10}$$

10. Sum of values (S):

$$S = \sum_t s(t), \tag{11}$$

where the summation is performed over a period of time.

11. Mean (μ):

$$\mu = \frac{1}{N}\sum_t s(t), \tag{12}$$

where N is the total number of samples.

12. Signal power (P):

$$P = \frac{1}{T}\lim_{t\to\infty}\sum_t |s(t)^2|, \tag{13}$$

where T is the time period.

13. Signal energy (E):

$$E = \sum_t |s(t)^2|. \tag{14}$$

2.4. Classification

The features are separated into different classes using different machine learning methods, which are generally categorized into supervised and unsupervised techniques. Different classification techniques have been successfully applied to EEG signal analysis such as K-nearest neighbour (KNN) [29], Bayesian classifier [30], multi-layer perceptron (MLP) [31], linear discriminant analysis (LDA) [32] and support vector machine (SVM) [33]. The following is a brief description of the supervised classification algorithms used in this study.

2.4.1. Support Vector Machine

A hyperplane is used in support vector machine to discriminate between different classes. This hyperplane is selected on the basis of margin maximization. The generalization capability of SVM is increased by maximizing the margins, that is the distance between the nearest training points. It is generally considered insensitive to problems such as over-fitting and the curse of dimensionality. This fact makes SVM suitable for the classification of expert-novice player classification. Linear, as well as non-linear analysis can be used for the EEG data [34]. The SVM algorithm uses the kernel trick to create non-linear decision boundaries, in which data are mapped to higher dimensional space by using a kernel function.

2.4.2. Naive Bayes Classifier

Naive Bayes is one of the simplest and easiest to implement statistical algorithms. It calculates the probability of each class member to assign them the best suited class. The method is based on the assumption that the attributes used are not dependent on each other, which helps in reducing the computational cost. A good classification performance has been observed with this underlying assumption [29]. The naive Bayes classifier assumes that the samples are contained in a training set C_k, having k class labels. For game player classification, there are two classes to be identified, including $C_1 = Expert$ and $C_2 = Novice$. $X_1, X_2, \cdots, X_n$ represents the samples, and $A_1, A_2, \cdots, A_n$ represents the n measured values of attributes represented by,

$$P(C_i|X) > P(C_j) \quad \text{for} \quad 1 \leq j \leq m, j \neq i, \tag{15}$$

where $P(X_1|Cj)$, $P(X_2|Cj)$, $\cdots$, $P(X_n|Cj)$ are the probabilities calculated from the training data.

2.4.3. Multilayer Perceptron

Neural network-based algorithms are widely used in data classification studies. A multi-layer perceptron has a three-layered structure, consisting of an input layer, a hidden layer and an output layer. The hidden layer could have multiple layers. In each layer, neurons are connected to the output of neurons from the immediately preceding layer. The neurons in the input and output layers only have outgoing and ingoing connections, respectively. The MLP algorithm is considered to be adaptable to a large variety of problems, but is sensitive to the problem of overfitting for noisy data. The inputs of neurons are mapped to the output using transfer functions such as sigmoid, rectified linear unit and hyperbolic tangent [35]. In this case, a sigmoid function has been used to determine the activity y_j with the help of a function of the total weighted input given as,

$$y_j = \frac{1}{1 + e^{-xj}}, \tag{16}$$

The total weighted input X_j of a unit is computed as,

$$X_j = \sum_i^n y_i W_{ij}, \tag{17}$$

where the level of activity and the weight between the i_{th} and j_{th} connection are represented by y_i and W_{ij}, respectively.

3. Experimental Results

The details about the experimental settings and performance analysis are presented in this section.

3.1. Configuration and Parameter Settings

The data are divided with a 70–30 ratio, where 70% of the data is used for training purpose and the remaining 30% data to test the proposed system. The experiments are performed on a core i5 system with 6 GB RAM. To classify the recorded EEG data into expert-novice level based on extracted features from the fourteen-channel headset, three different classification algorithms were trained, including naive Bayes, SVM and MLP. The MLP used in this study consists of a hidden layer with 15 neurons, and the network is fully connected such that all neurons in each layer have a connection with all neurons in the following layer. The network is trained using the back-propagation algorithm, and cross entropy is used as the cost function. The weights are initialized randomly from a zero mean Gaussian distribution. The learning follows the stochastic gradient descent (SGD) algorithm and selects the optimized weights for the neuronal connections giving an accurate classification of game player expertise level. The network hyper-parameters including the learning rate are selected using grid search. For the SVM classifier, a linear kernel is used.

3.2. Channel Selection

A statistical analysis is performed to select the most significant channels for classifying the expertise level. A box-plot for the normalized power spectral densities (PSDs) of the fourteen EEG channel recordings for expert and novice players is shown in Figure 5. The + symbol indicates the outliers, and the red lines within the box represent the median value. The rectangular box lies in between the first and third quartile of the data values. The results show that on average, expert players have more brain activity as compared to novice players. A t-test is applied on the PSD values of expert and novice players. A t-test is used to compare the averages of two results, and the resulting t-score and p-value are a measure of the significance of the results. A p-value of less than 0.005 indicates that the difference between averages is significant and not by chance. The results show that only channels $F7$, $O1$, $F4$ and $AF4$ are significant for the purpose of player classification with a p-value < 0.005.

The data of fourteen channels are also analysed on the basis of their activity using brain visualizations. Figure 6 shows the brain activity maps of the average power spectral densities for each channel of an expert and novice player. The colours in the figure represent brain activity as depicted using the PSD, where shades of blue show no or lesser activity, which increases as the colour turns red. It is evident that channels $F7$, $O1$, $F4$ and $AF4$ are most active during game play of the expert player and do not show a significant activity in the case of the novice player. This further adds credence to the statistical analysis for which the results were presented earlier. This clearly shows that the activities of the frontal and occipital regions are responsible for determining the expertise level in video game play. The frontal lobe is involved in cognitive aspects and decision making. The major portion of the occipital lobe deals with visual functions. The features mentioned in Equation (2)–Equation (14) are used for the selected channels, which are then used to train the set of classifiers as is done for the fourteen channels.

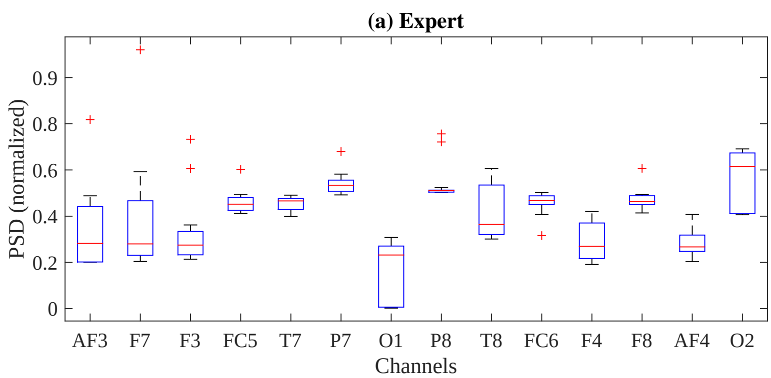


Figure 5. *Cont.*

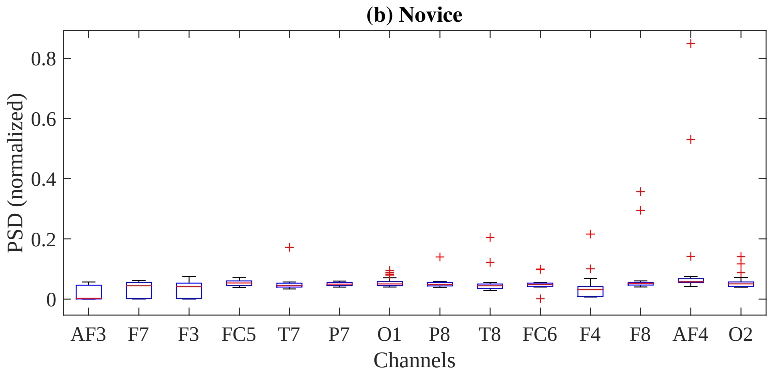


Figure 5. Box-plot for the normalized power spectral densities of fourteen EEG channels for (**a**) expert players and (**b**) novice players. The + symbol represents the outliers; the rectangular box shows the region between the first and third quartile; and the red line shoes the median values.

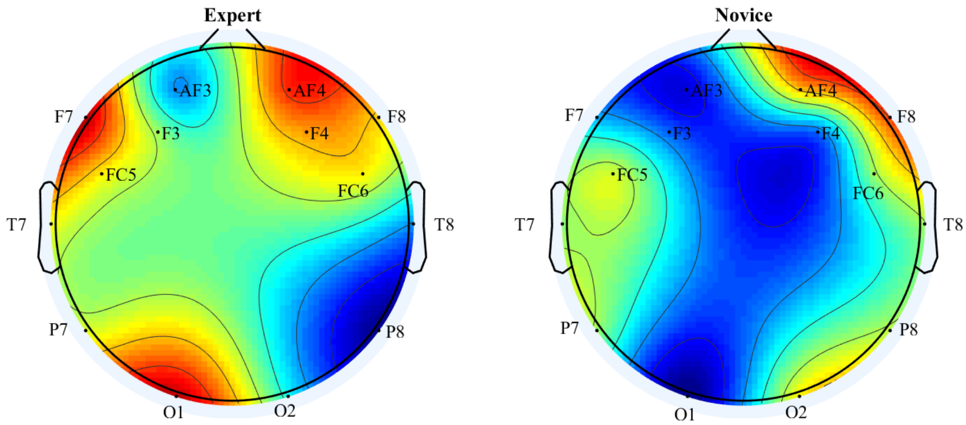


Figure 6. Brain visualization using the average power spectral density for an expert and a novice player.

The brain maps are also visualized for the expert and novice player during the resting state. The results are shown in Figure 7. During resting periods, players were instructed to relax, and no mental task was performed. The baseline EEG is recorded with eyes open, and the brain maps show the corresponding activity on the frontal and occipital regions.

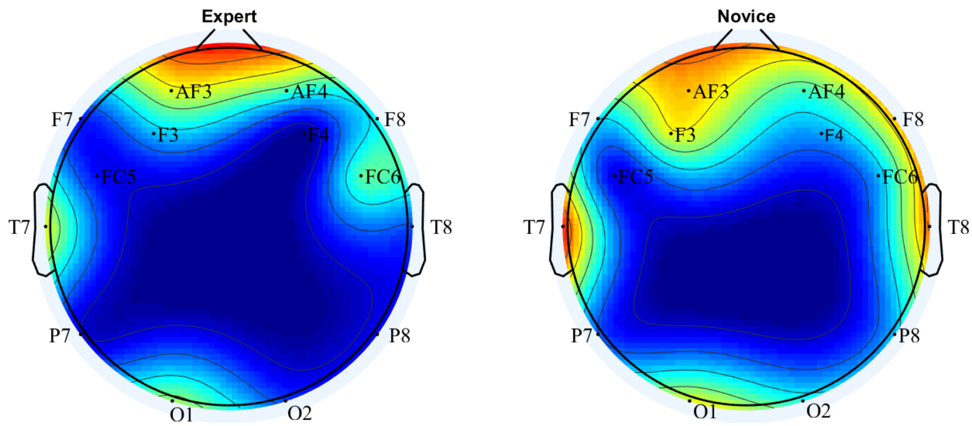


Figure 7. Brain visualization for baseline activity using the average power spectral density for an expert and novice player.

3.3. Performance Analysis

The performance of these algorithms is evaluated using different performance metrics for both cases, i.e., by using data from all fourteen EEG electrodes and those selected channels that give higher activity. The performance parameters include classification accuracy, computation time, kappa statistic, precision, recall and area under the curve (AUC) of the receiving operator characteristic (ROC) curve. Cohen's kappa statistic is used to measure the inter-observer agreement and has a value that ranges between zero and one. A value close to zero represents agreement by chance, and a value closer or equal to one represents near perfect or perfect agreement. For a classification task, precision is defined as,

$$precision = \frac{TP}{TP + FP}, \tag{18}$$

where TP and FP represent the true positive and false positive values, respectively. The recall value is calculated as,

$$recall = \frac{TP}{TP + FN}, \tag{19}$$

where FN represents the false negative values. The AUC of the ROC curve represents the classification performance of a classifier. A value closer to one shows that the classifier has a good performance.

The results are presented in Table 2 and show an accuracy of 88% for the naive Bayes classification when data from all fourteen available channels are used. Moreover, the naive Bayes algorithm classified the data in 0.03 seconds. The kappa statistic of 0.6218 is achieved by both the SVM and MLP, which is 0.1 greater than the naive Bayes classifier. On the other hand, MLP takes the longest time to build when the fourteen channel data are used. Table 2 also shows the results for the selected performance parameters when four significant channels are selected. It is evident that the performance parameters of the four-channel classification have a slight difference as compared to the fourteen-channel case. In particular, the classification accuracy improves for SVM and MLP and is slightly reduced for naive Bayes. The time taken for all algorithms is now reduced to acceptable levels for real-time applications except for MLP, which is still comparatively higher. SVM gives the best classification accuracy of 86% with a classification time of 0.04 s with four channels. This shows that by selecting the significant channels, both SVM and naive Bayes can be reliably used for player classification in less time.

Table 2. Performance parameters of classification algorithms using the four selected channels and all fourteen available channels.

Number of Channels	Classification Algorithm	Correctly Classified	Incorrectly Classified	Time Taken (s)	kappa Statistics	Precision	Recall	ROC
4 channels	Naive Bayes	84	16	0.01	0.6543	0.839	0.84	0.881
	SVM	86	14	0.04	0.6998	0.859	0.860	0.846
	MLP	84	16	0.94	0.6604	0.840	0.840	0.900
14- channels	Naive Bayes	88	12	0.03	0.7356	0.886	0.880	0.899
	SVM	82	18	0.10	0.6218	0.822	0.820	0.821
	MLP	82	18	7.5	0.6218	0.822	0.820	0.907

Figure 8 shows the performance of the algorithms used in terms of mean absolute error (MAE), root mean squared error (RMSE), relative absolute error (RAE) and root relative squared error (RRSE) using fourteen and four channels. The MAE is calculated using,

$$MAE = \frac{\sum_{i=1}^{n} |o_i - b_i|}{n}, \tag{20}$$

where n is the number of observations and o_i and b_i are the observed and actual values, respectively. The RMSE is calculated using,

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(o_i - b_i)^2}{n}}, \tag{21}$$

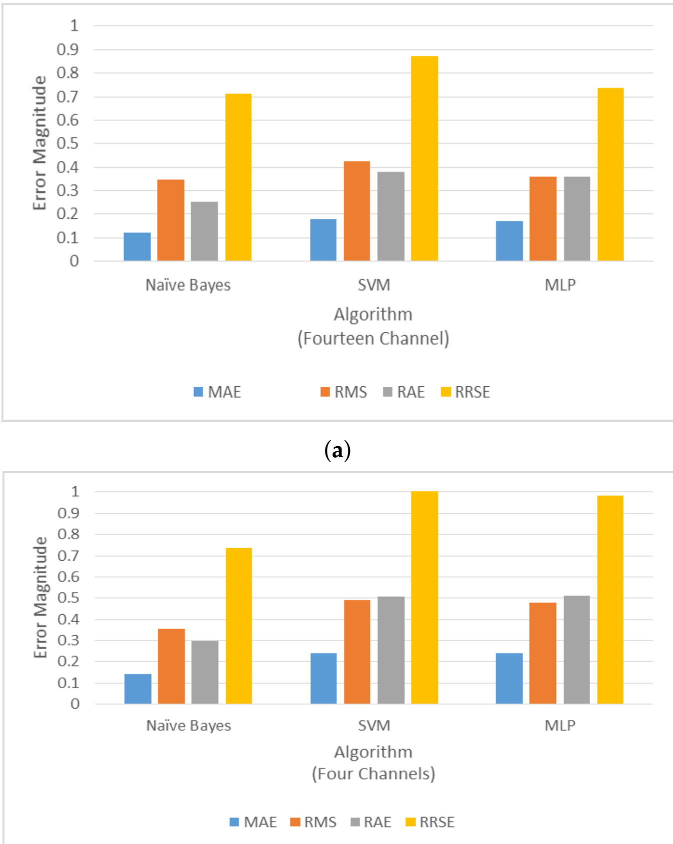
The RAE is calculated using,

$$RAE = \frac{\sum_{i=1}^{n}|o_i - b_i|}{\sum_{i=1}^{n}|\bar{o}_i - b_i|}, \tag{22}$$

where $\bar{o}_i$ is the mean of o_i. The value of RRSE is calculated using,

$$RRSE = \sqrt{\frac{\sum_{i=1}^{n}(o_i - b_i)^2}{\sum_{i=1}^{n}(\bar{o}_i - b_i)^2}}. \tag{23}$$

It is clear from Figure 8a that the naive Bayes classifier gives the minimum error magnitude for all the error measuring parameters as compared to other classifying algorithms. Figure 8b shows the error performance of the algorithms used in four-channel classification. It can be observed that error performance in the case of fourteen channels is slightly better, but in the four-channel case, the computational cost has been reduced. Feature vector reduction has resulted in the reduction of the time taken by each classifier. Moreover, there is not much difference in terms of the kappa statistic.



(**a**)

(**b**)

Figure 8. Error magnitudes of different algorithms used: (**a**) fourteen channels; (**b**) four selected channels with higher activity.

4. Conclusions

The expertise level of a game player on a consumer-based gaming device has been classified using EEG recordings, where the classification is based on the brain activity recorded using a wearable EEG device. Multiple classifiers are used to classify the player's expertise level during game play on a smart phone, by extracting thirteen morphological features from the recorded EEG data. Among the classifiers, the naive Bayes algorithm has given the best error performance, as well as accuracy, computation time and kappa statistic for both fourteen- and four-channel classifications, although SVM also gave good accuracy and computation time for four-channel classification. These results show that the naive Bayes and SVM classifier have the potential to be used in gaming applications, which can suggest the player's expertise level from EEG data recordings. On the basis of brain activity maps, four significantly active channels are identified for classification instead of all fourteen channels. A small difference is observed between the two cases in terms of performance and error parameters, whereas using four channels has reduced the computational cost. In combination with only a minor difference in the kappa statistic, we can say that the four-channel approach is a more suitable candidate with a good balance between performance and complexity. In future, we plan to predict the score of the mobile game player by recording his/her EEG activities and applying regression-based techniques. This can be applied to make mobile games more attractive for users and also used to assess the effectiveness of training a subject in educational applications and game analytics. The number of subjects will also be increased in future studies, and players will be analysed for multiple game genres.

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