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Application of Hybrid Metaheuristic Algorithms for Feature Selection in Event-Related Potential Classification in Problematic Gamers Using Electroencephalograph Signal

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ABSTRACT Online games have become a popular form of entertainment, particularly for relieving stress, and the rise in online gaming has led to an increase in problematic gaming behaviors. Excessive use of the internet for gaming has raised concerns about its neurophysiological impact, particularly on cognitive and emotional functions. Electroencephalogram (EEG) and Event-Related Potential (ERP) analysis are valuable tools for monitoring these effects. Given the vast amount of features that can be extracted from EEG signals, it is crucial to apply efficient feature selection methods to identify the most informative ones. This study utilizes the Go/No-Go Association Task (GNAT) combined with the recording of 16-channel EEG signals, chosen as the data-recording method to observe the response of individuals who are problematic online gamers to several stimulus themes. The participants in this study were individuals identified as problematic gamers, with verification conducted by psychologists to ensure their eligibility as research subjects. In this context, metaheuristic algorithms like Genetic Algorithm (GA), Ant Colony Optimization (ACO), and Particle Swarm Optimization (PSO) are employed to enhance feature selection. A hybrid approach, combining one of these methods with Binary Stochastic Fractal Search (B-SFS), is proposed to improve classification accuracy and optimize feature selection. The results demonstrate that the hybridization of the best algorithm with B-SFS successfully selects the optimal features, achieving perfect classification performance, with an accuracy, sensitivity, and specificity of 1.00 for all respondents. This emphasizes the effectiveness of B-SFS, particularly its diffusion process, where Gaussian distribution facilitates the search for the best solution, thereby improving the reliability of feature selection for detecting problematic gaming behavior.

INDEX TERMS Electroencephalograph, Event-Related Potential, Go/No-Go Association Task, Metaheuristic Algorithm, Problematic Online Gamers

I. INTRODUCTION

Games are a form of entertainment that is popular among people of all ages for relieving stress. Online games have become a popular choice because of their features that offer limitless competitive experiences, complex narratives and characters, as well as opportunities to socialize with other players via the internet connection [1]. The growing interest in online games has been increasing every year. According to the Digital 2024 report, Indonesia ranks first in the world for the number of online game players in the age range of 16-64 years, with a percentage of 96.5%. This increase has a positive impact on the economy. In 2024, the video game market in Indonesia is projected to generate a revenue of USD 1.232 million, with an annual growth rate of 7.32% until 2027. The increased availability of affordable internet and widespread use of hardware have made Indonesia one of the largest and most promising video game markets in Southeast Asia, with an estimated 53.8 million gamers by 2027 [2].

However, the rise in online game players has also brought about a challenge, one of which is the increase in players who excessively use the internet, leading them to become problematic game players. According to research by Lopez-Fernandez et al. [3], Indonesia has a problematic internet use rate of 4.7%, the highest compared to fifteen countries from

Europe, America, and Asia, with a specific problematic gaming rate of 4%. According to research by Shi et al. [4], individuals who repeatedly and persistently play video games not just for fun but as an important activity to cope with life's stress are prone to becoming problematic game players. The problematic gaming behavior exhibited by these players can lead to various risks, such as addiction, increased tolerance towards playing needs, and decreased interest in other activities. Zajac et al. [5] and Kashif et al. [6] confirm that video game addiction is related to various psychological issues, such as sleep disorders, decreased daily performance, and Attention Deficit Hyperactivity Disorder (ADHD). In some cases, this condition can even lead to serious consequences such as seizures or death caused by gaming activities. This addiction is referred to as Behavioral Addiction, which makes the sufferer vulnerable to various factors such as psychological conditions, stress, environment, and easy access to games, ultimately forming a harmful playing pattern [1]. These findings highlight the importance of monitoring and managing gaming behavior, which can be done using Electroencephalogram (EEG) to monitor the neurophysiological impacts of problematic gaming.

Neurophysiological studies on problematic gaming in Internet Gaming Disorder (IGD) and Internet Addiction Disorder (IAD) provide insights into the neurocognitive mechanisms underlying the risks faced by problematic players. The use of Electroencephalogram (EEG) has been widely used to investigate addictive behavior, offering the advantages of accessibility, low cost, and excellent temporal resolution [7]. One technique that can help in EEG analysis is Event-Related Potential (ERP). ERP provides a direct measurement of neural activity that occurs quickly after a stimulus, response, or other event. Various ERP components have been identified and validated as measures of sensory, cognitive, affective, and motor processes [8]. ERP can be used to understand how problematic gaming behavior affects the brain, especially in cognitive and affective aspects.

To obtain more relevant and accurate information from ERP, a feature extraction technique is needed on EEG signals to identify important patterns or information in brain activity. However, with the large number of features that can be extracted from EEG signals, it is important to select a subset of features using an efficient method to identify the most informative features [9]. According to Torres et al. [10], feature selection plays a crucial role in improving model quality because it can eliminate redundant or irrelevant features, reducing the risk of overfitting and preventing predictions based on noise. This approach contributes to higher classification accuracy by focusing the data on the most relevant features.

Metaheuristic algorithms have been applied in several studies to aid in the feature selection process. For example, Samrudhi et al. [11] used the Harmony Search algorithm for feature selection in EEG signals for Motor Imagery classification, achieving an accuracy of 92.49% with KNN. Zina et al. [12] applied Particle Swarm Optimization (PSO) for optimizing EEG feature selection in emotion recognition, achieving an accuracy of 86.63% using an SVM model. Oluwagbenga et al. [13] compared several metaheuristic algorithms, including Ant Colony Optimization (ACO), Genetic Algorithm (GA), Cuckoo Search Algorithm (CSA), and Modified PSO (M-PSO) for feature selection, concluding that M-PSO achieved the best performance with an accuracy of 88% and faster convergence (under 50 iterations). Thirumal et al. [14] employed the hybrid Greedy River Formation Dynamics (RFD) method for feature selection in autism spectrum classification, achieving an accuracy of 97.15%. Metaheuristic algorithms have proven highly effective, yet they bring practical challenges, particularly when selecting the most efficient algorithm for finding optimal features and adjusting parameters [15]. To address these issues, this study proposes a metaheuristic-based feature selection method specifically designed to enhance classification accuracy in EEG data for problematic gamers. By employing a hybrid approach, the method aims to overcome the difficulties commonly associated with parameter tuning, enabling the selection of the most informative subset of features and strengthening the reliability of predictions related to problematic gaming.

This study focuses on investigating the neurophysiological impacts of problematic gaming behavior in Indonesia, where online gaming participation has significantly increased. By utilizing Electroencephalogram (EEG) and Event-Related Potential (ERP) analysis, the research seeks to gain insight into how excessive gaming affects cognitive and emotional brain functions. Additionally, this work aims to develop effective feature extraction and selection techniques to improve predictive accuracy for problematic gaming behavior. Identifying the most relevant features in EEG signals will help lay the groundwork for future interventions and preventive strategies to address the risks associated with gaming addiction.

II. MATERIALS AND METHOD

This study utilizes the Go/No-Go Association Task (GNAT) in combination with the recording of 16-channel Electroencephalogram (EEG) signals, which was selected as the data collection method to observe the neural responses of individuals identified as problematic online gamers in response to various stimulus themes. The GNAT requires participants to respond as quickly and accurately as possible, which provides a controlled setting to measure the cognitive and emotional responses of participants. During this task, EEG signals were recorded to capture brain activity while participants engaged in the test, allowing for the analysis of neural processes associated with decision-making, impulsivity, and attention.

Data collection followed strict ethical guidelines established for research involving human subjects to ensure the protection and rights of the participants. Prior to the commencement of data collection, ethical approval was obtained from the relevant ethical committee, with consent given by participants based on the ethical approval document number 148/2024 Etik/KPIN issued by the Scientific

Psychology Consortium of Nusantara, Indonesia. This ensured that the study adhered to the necessary ethical standards, including obtaining informed consent from all participants, maintaining confidentiality, and ensuring that participant's well-being was safeguarded throughout the research process.

A. PARTICIPANT SELECTION

This study focuses on EEG data collection from young adult respondents aged 18-25 years who are active in playing competitive online games such as Valorant®, Mobile Legends®, PUBG®, and others. The selection of respondent criteria is based on recommendations from psychologists according to relevant literature. The chosen criteria include consistent participation in online gaming for the past 12 months, daily involvement in online gaming sessions, and gaming duration between 4 to 10 hours per day [16].

The respondent selection process began with filling out a questionnaire and participating in an interview conducted by psychologists. These assessments were designed to evaluate whether the respondents met the predefined criteria and to classify them into either the *non-problematic gamer* or *problematic gamer* group. Based on the evaluation results, a total of 19 respondents were selected for EEG data collection, consisting of 10 problematic gamers (denoted as "PR") and 9 non-problematic gamers (denoted as "N").

B. GO/NO GO ASSOCIATION TASK (GNAT)

The instrument employed for measurement was the GNAT (Go/No Go Association Task), specifically designed to evaluate implicit association variables. This computer-based assessment tool employed a software to produce stimuli aligned with the study's aims. The GNAT is a cognitive assessment employed in psychology and neuroscience to evaluate response inhibition. Participants must press a button in response to a designated stimulus (Go signal) and abstain from responding to an alternative stimulus (NoGo signal). In the GNAT procedure, the instrument introduces two categories of stimuli: targets and distractors [17],[18].

FIGURE 1. Displays the stimulus view on GNAT,

GNAT is designed as shown in FIGURE 1 where the stimulus word is displayed in white in the center of the screen against a black background. Each session on GNAT contains 60 stimulus words, divided into two categories: target words and non-target words. Each word is displayed for one second [18]. Target words represent stimuli that reflect the theme or category associated with the session's theme, while non-target words do not correspond to the theme. The order of target and non-target words in each session is randomized, so each respondent receives a different sequence. During the Go/No-Go Association Task (GNAT), participants must hit the spacebar to indicate "Go" when a target word is presented and refrain from pushing any key to signify "No Go" when a distractor word is displayed [19]. Participants were required to complete five tasks, consisting of one practice session and four main sessions. During the practice session, participants were introduced to the overarching GNAT procedure, which involved the presentation of stimuli and instructions for responding to relevant stimuli. In the main sessions, four target words were used by respondents in their responses. The focus of session one was Academic, session two was Game, session three was Work, and the final session pertained to Relationships. These four sessions were chosen based on a focus group discussion conducted by the Tel-U Research Team and psychologists to determine appropriate stimuli for observing the impact of online gaming on players. During this session, members of Tel-U Esports, an online gaming student organization at Telkom University, were also invited to discuss and help determine the stimuli, covering both in-game and out-of-game activities. As a result, the discussion identified four themes considered suitable as stimuli: Academic, Game, Work, and Relationships.

These themes were selected based on insights and conclusions from psychologists, as they represent the aspects most affected by problematic gaming behavior. For the Academic and Work themes, individuals exhibiting problematic gaming tendencies often neglect these responsibilities and show slower responses when confronted with related stimuli. Conversely, when presented with stimuli related to the Game theme, problematic gamers tend to display heightened sensitivity and quicker responses, consistent with their excessive engagement in gaming activities. Lastly, the Relationships theme was included because psychologists observed that problematic gamers are often more sensitive to interpersonal relationships, reflecting the social challenges associated with their behavior. These four themes were subsequently used in four separate sessions for data collection to comprehensively assess the behavioral impact of online gaming.

During the GNAT process, psychologists monitored the participant's behavior and bodily movements. In GNAT, the potency of an association is assessed by examining the proximity of objects, such as words, to the target category.

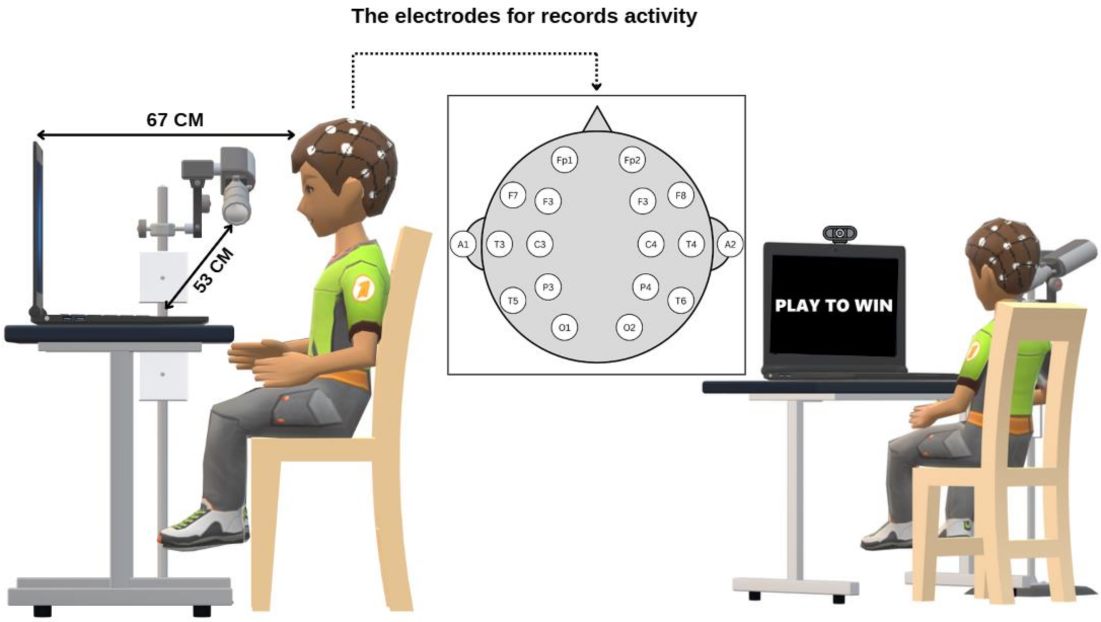

FIGURE 2. Illustration of room arrangement and EEG recording conditions [20],

Furthermore, stimuli that are not directly associated with the target words may function as distractors unrelated to the target words. One condition entails the concurrent detection of stimuli denoting the target category and distractors [18], [19].

B. RECORDING SETUP

Data recording was performed at the Smart Data Sensing Laboratory of Telkom University, Bandung. The EEG recording device used in this study was the Contect KT-88, which is 16 electrodes placed according to the 10-20 standard with sampling frequency of 100 Hz. Data collection consisted of three stages: initial interviews, GNAT task performance and EEG signal recording, and final interviews.

In the initial interview, respondents filled out written consent forms containing details about the research objectives, potential risks, and benefits. This interview was conducted by psychologists to verify the respondent's personal data. Additionally, the interview included questions about the online games the respondents played, as well as their gaming duration. Respondents were also allowed to inspect the room where data collection would take place and were given an explanation about the technical aspects of the data collection process.

After the interview, respondents were guided to the data collection room. In this room, the respondents were fitted with an electrode cap for EEG signal recording during the GNAT task, as illustrated in FIGURE 2. The layout of the devices in the illustration is based on an experiment by Wijayanto et al. [20]. The setup was designed to ensure that participants were comfortable throughout the recording process. The monitor screen, used as the test medium, was positioned 67 cm from the participant. This distance was chosen because it aligns with the recommended comfortable working distance for monitor screens, which is between 45 and 75 cm according to the American Optometric Association [20],[21]. The room lighting was deliberately dimmed to help participants concentrate on the GNAT task without interference from excessive brightness. Environments with high illuminance and elevated correlated color temperatures (CCT) can be overly intense, disrupting normal attention processing [23], [24], [25]. This may impair concentration, make individuals more prone to distractions during sustained attention tasks, and ultimately reduce task efficiency [26].There should be no distractions, such as noise or light, which could affect the EEG signal recording results. Any distractions can influence the quality of the EEG signal recording.

In this data collection phase, in addition to EEG signal data, the respondent's GNAT task performance and two additional videos were recorded. The first video recorded the respondent's face, while the second video focused on the keyboard. The video recordings included a shot of the participant's face on the right side and the GNAT screen on the left side, as shown in FIGURE 3. Timestamps in the format hh:mm,ms (e.g., 00:03:00:73) were included to assist psychologists in analyzing non-verbal responses and the responses provided during the GNAT task when the respondent pressed the spacebar.

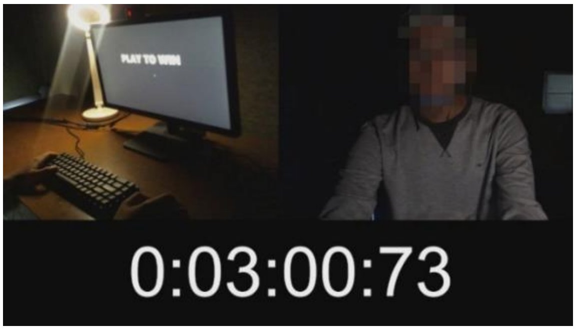

FIGURE 3. Video recording results during data collection.

Once the data collection was completed, the respondents were directed back to psychologists for the final interview.

This interview included questions regarding the respondent's experiences during the GNAT task. The results of the initial and final interviews were used by psychologists as additional observations for each respondent.

C. EEG DATASET

In this study, we introduced another dataset of the TelUnisba Neuropsychology EEG Dataset (TUNDA), known as TUNDA 2.0. This dataset focuses on the EEG signal results from problematic respondents. However, not all respondents can be used based on validation results from psychologists, so only the following respondents are included in this dataset: PR 02, PR 04, PR 06, PR 07, and PR 09. The dataset contains five EEG signals with 16 channels based on the montage in Figure 2 from the first and second sessions of the GNAT task performed by problematic gamer respondents. The signals have not undergone signal processing, meaning they still contain noise, such as random fluctuations, as shown in FIGURE 4. Because of this, the EEG data must undergo preprocessing steps, such as filtering, artifact rejection to remove eye artifacts, and segmentation to isolate the EEG signal for each word stimulus.

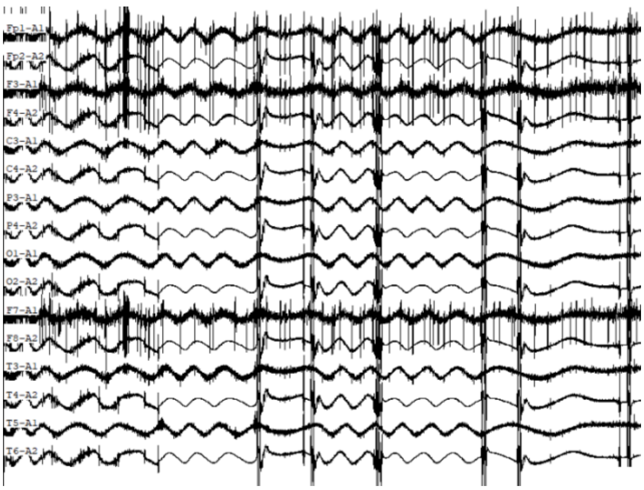

FIGURE 4. EEG signal recording results.

D. INDEPENDENT COMPONENT ANALYSIS (ICA)

Independent Component Analysis (ICA) is a prevalent technique in signal processing employed to identify and remove noise elements, such as body movements and eye blinks, that may remain in electroencephalogram (EEG) signals despite filtering [24], [25]. Considering that the data collection technique requires responders to maintain continuous attention on a computer screen without interruptions, the acquired EEG signals are likely to exhibit ocular artifacts. The artifacts, such as voltage distortions from eye rotation, muscle contractions, and blinking, can disrupt analysis due to their amplitude being considerably greater than the neural signals associated with specific events and are frequently correlated with the conditions of data collection. This study exclusively eliminates components associated with ocular artifacts, including eye blinks and eye movements. Consequently, eliminating visual artifacts is crucial to avert data misunderstanding. In ICA, the activity of each signal channel is sampled and evaluated randomly [26], [27].

ICA employs a statistical approach to transform an observed multidimensional random vector into components that are as statistically independent from one another as possible. The mathematical formulation of ICA involves several key steps and can be expressed using Eq. (1), while the signal source matrix S is represented by Eq. (2) [26]. In these equations $a, b, c,$ and d refer to the mixing coefficients. The objective of ICA is to estimate both A and S based on the observed data X, ensuring that the components in S are as statistically independent from one another as possible[26].

$$X = \begin{pmatrix} X_1 \\ X_2 \end{pmatrix} = \begin{pmatrix} as_1 + bs_2 \\ cs_1 + ds_2 \end{pmatrix} = \begin{pmatrix} a & b \\ c & d \end{pmatrix} \begin{pmatrix} s_1 \\ s_2 \end{pmatrix} = As \quad (1)$$

$$S = \begin{pmatrix} s_1 \\ s_2 \end{pmatrix} = \begin{pmatrix} (s_{11}, s_{12}, \dots, s_{1N}) \\ (s_{21}, s_{22}, \dots, s_{2N}) \end{pmatrix} \quad (2)$$

E. BUTTERWORTH BANDPASS FILTERING

The raw EEG signals had substantial noise, including components from muscle activation, power line interference, and eye movement. A Butterworth bandpass filter was employed on the EEG signals to attenuate undesirable frequency components and eliminate noise. A fourth-order Butterworth filter is employed. A fourth-order Butterworth filter was selected due to its superior linear response relative to alternative filters. The utilized cutoff frequencies are below 1 Hz and above 40 Hz. Frequencies below 1 Hz were excluded due to their classification as low-frequency noise, including baseline drift or gradual signal shifts, while frequencies beyond 40 Hz were discarded to mitigate sinusoidal interference commonly observed at elevated frequencies [28], [29]. The general transfer function $H(s)$ of a Butterworth filter is expressed in Eq. (3) [30], where ω_c represents the cutoff frequency, n denotes the order of the filter.

$$H(s) = \frac{1}{\sqrt{1+\left(\frac{s}{\omega_c}\right)^{2n}}} \quad (3)$$

For a bandpass Butterworth filter, the transfer function combines both lowpass and highpass characteristics. The transfer function for a bandpass Butterworth filter is given by Eq. (4) [30], where ω_L is the lower cutoff frequency, and ω_H is the upper cutoff frequency. These frequencies must be converted from Hz to radians per second using Eq. (5) and Eq. (6) [30].

$$H(s) = \frac{\left(\frac{s}{\omega_L}\right)^n \left(\frac{s}{\omega_H}\right)^n}{\left(1+\left(\frac{s}{\omega_L}\right)^{2n}\right)\left(1+\left(\frac{s}{\omega_H}\right)^{2n}\right)} \quad (4)$$

$$\omega_L = 2\pi \times lowcut \quad (5)$$

$$\omega_H = 2\pi \times highcut \quad (6)$$

E. ERP CLASS LABELING

Event-Related Potential is a direct measurement of brain activity used to understand various cognitive, affective, sensory, and motor processes. ERP reflects shifts in EEG signal waves that represent the brain's response to a particular stimulus [34], [35]. The early waves in ERP, which typically occur within 100ms after the stimulus begins, are associated with unconscious sensory processing of the given stimulus. The subsequent stage in the ERP signal, which occurs after 200ms, is related to controlled attention, memory access, and integrative processing of the stimulus [35]. P300 is one of the components of ERP that appears as a response to active involvement in detecting target stimuli relevant to a task [35]. The ERP P300 can be detected by identifying the time point that contains the maximum value within the 200-500 ms range after the stimulus, as illustrated in FIGURE 5 [36].

The ERP determination process is not performed for the entire session but only for Session 1 with the academic stimulus and Session 2 with the game stimulus. After the EEG signals have undergone decomposition and filtering, the next step is ERP determination, by labeling them as "ERP" and "No ERP." Before the signal is labeled, the signal is segmented based on the time range from when the stimulus appears until the respondent provides a response. This segmentation is applied only to the target words that were answered correctly by the respondents, so not all stimuli are processed in the ERP search.

Since the ERP component to be analyzed is P300, the segmented data then searches for the highest peak within the 200–500 ms time range. If the EEG signal duration is less than 200 ms, the data will not be further processed in the ERP search, as it does not meet the required time range for P300 component detection. If the signal duration is greater than 200 ms but less than 500 ms, linear interpolation for upsampling is applied to the signal.

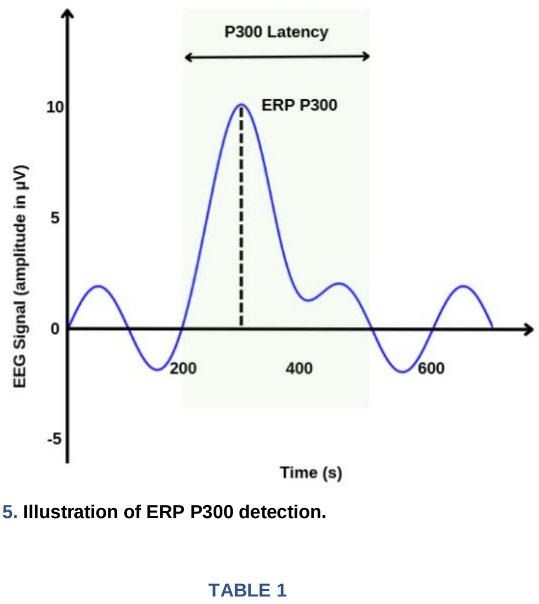

FIGURE 5. **Illustration of ERP P300 detection.**

TABLE 1
Amount of data per respondent

Respondent	Amount of Data	
	ERP	No ERP
PR 02	109	251
PR 04	74	256
PR 06	61	257
PR 07	211	113
PR 09	184	140

ERP observation is usually performed at three midline electrode locations: frontal, central, and parietal [35]. However, since the electrodes used during data collection do not cover the midline locations, ERP observation is represented by electrodes on the right and left sides: F3, F4, C3, C4, P3, and P4. ERP labeling is performed separately for each of these six channels to ensure that the ERP response can be detected specifically in each of these channels.

ERP determination is based on the highest amplitude within the 200–500 ms range with a voltage between 6.5–20 μV [35], [37]. If a peak within this range has an amplitude between 6.5 – 20 μV, the signal is labeled “ERP.” If no peak is detected within this range, the signal is labeled "No ERP." TABLE 1 shows the amount of data for each respondent in the "ERP" and "No ERP" classes.

F. FEATURE EXTRACTION AND FEATURE SELECTION

The important information from the EEG signal after the pre-processing stage will be represented as features. A statistical approach is one of the simplest and commonly used methods in feature extraction because it can provide basic information from the data. However, this approach alone is not sufficient to explore all the information contained within the EEG signal [26]. Therefore, in addition to using statistical features (Mean, Standard Deviation, Skewness, Kurtosis, Min, Median, Peak Latency, Variance), this study also uses additional features such as power and Hjorth Parameters (Hjorth Mobility and Hjorth Complexity), adapted from the studies of Bablani et al. [38], Nawaz et al. [39], Qaisar et al. [40], and Ahmad et al [41].

In building a machine learning model, the input information must accurately reflect brain activity, which requires selecting the most relevant and optimal feature subset. Therefore, an additional step is needed to obtain this subset, known as feature selection. Feature selection can eliminate irrelevant variables, reduce computational complexity, decrease overfitting, and prevent the model's generalization capacity from being compromised [35]. In this study, the hybrid approach combines baseline metaheuristic algorithms specifically the Genetic Algorithm (GA), Ant Colony Optimization (ACO), and Particle Swarm Optimization (PSO)—with Binary Stochastic Fractal Search (B-SFS) to enhance the feature selection process. The primary objective is to leverage the strengths of these algorithms to explore and exploit the solution space, while using B-SFS to refine the solutions through a diffusion process illustrated in FIGURE 6.

To begin with, the baseline metaheuristic algorithms (GA, ACO, or PSO) perform the initial exploration and exploitation phases. During the exploration phase, the algorithms search through the feature space to identify potentially optimal feature subsets, while during the exploitation phase, they focus on fine-tuning these subsets to improve their performance. Once this is done, B-SFS is integrated into the process to further optimize the feature selection. The B-SFS method works by simulating a diffusion process that helps in navigating the feature space more effectively, allowing for the discovery of better feature subsets that might not have been reached using the baseline algorithms alone.

The hybridization framework essentially combines the robust search capabilities of the baseline algorithms with the refinement power of B-SFS, leading to more efficient and effective feature selection. This hybrid approach aims to enhance the overall performance of the feature selection process by ensuring that both exploration and exploitation are balanced and that the solutions are further optimized in a manner that is not possible using any single method alone.

The evaluation of the hybrid approach is conducted through the calculation of fitness, a key metric used to assess the quality of the selected features. Fitness functions help determine how well a particular feature subset contributes to the overall performance of the model, ensuring that the chosen features are both relevant and effective for the task at hand. By using fitness calculations, the study ensures that the hybrid method provides measurable improvements in the feature selection process, ultimately leading to better model performance.

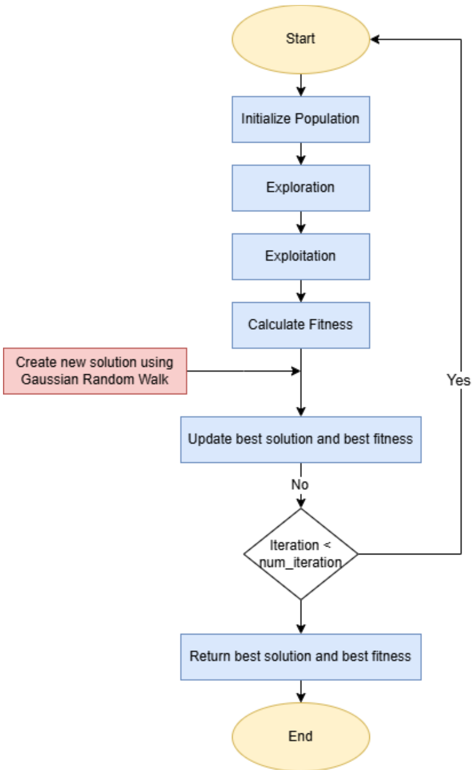

FIGURE 6. Flowchart of Hybridization Metaheuristic Algorithm

G. BINARY STOCHASTIC FRACTAL SEARCH

The Binary Stochastic Fractal Search (B-SFS) algorithm is a metaheuristic approach that is used in this study as a hybrid method to address challenges in feature selection. This algorithm leverages Binary Search to handle the search space issue in feature selection by converting continuous values into binary form, enabling more effective feature selection. By combining this binary search mechanism with Stochastic Fractal Search (SFS), B-SFS enhances the ability to explore and exploit the solution space efficiently.

In B-SFS, the diffusion process from SFS plays a key role in performing the exploitation task, guiding the algorithm towards promising solutions. Meanwhile, the update process is responsible for exploration, allowing the algorithm to search for optimal solutions across a broader solution space. This combination ensures that the B-SFS algorithm can avoid local optima and select the most relevant features for classification tasks, improving the overall accuracy of the model [36]. ALGORITHM 1 is the B-SFS pseudocode used this study based on [44], [45] with adjustments to meet the requirements of the study.

ALGORITHM 1 Proposed B-SFS for Hybrid method in Feature Selection

```
Input: Set of initial solutions S, Data X, Labels y, Maximum iteration
(max_iteration), Threshold (threshold)
Output: Best solution (best_solution), Best fitness score (best_fitness)
best_solution ← None
best_fitness ← 0
for iteration ← 1 to max_iteration do
    new_solutions ← empty list
        for each solution in S do
            new_solution ← solution
            flip_index ← random integer between 0 and length of solution
            new_solution[flip_index] ← 1 – new_solution[flip_index]
            Flip the bit at flip_index
            fitness ← fitness_function(new_solution, X, y, threshold)
            if fitness > best_fitness then
                best_fitness ← fitness
                best_solution ← new_solution
            end if
            append new_solution to new_solutions
        end for
        S ←new_solutions
end for
return best_solution, best_score
```

III. RESULT

The recorded data split into two categories “ERP” and “NO ERP.” In the "ERP" category contains EEG data that has a peak amplitude between 6.5 – 20 µV in the time range 200-500 ms. While the "NO ERP" category contains data that does not show a peak in that range.

A. NOISE COMPONENT REMOVAL

In this dataset, ICA was implemented using the EEGLAB toolbox in MATLAB. The ICA function in EEGLAB can decompose the EEG signals on each channel and assess their quality. This process helps determine whether the signal contains components from brain activity or artifacts. In channels where the signal includes ocular components, indicated by the "Eye" label, those components are removed to ensure only brain activity-related signals remain. In the signal processed with ICA, the numerous spikes seen in the raw signal in Figure 3 will be removed, resulting in a cleaner signal, as shown in Figure 7. Figure 7 shows the EEG signal plot after the ocular artifact components have been removed.

B. FILTERING USING BUTTERWORTH

Although ICA has been applied to remove ocular artifacts typically present at a frequency of 40 Hz [37], additional filtering is still needed to further enhance the quality of the EEG signal obtained. In FIGURE 7, even after ocular artifacts have been removed, low-frequency noise remains, as well as sinusoidal signals. To address this noise, a 4th-order Butterworth filter with a cutoff frequency range of 1–40 Hz is used. FIGURE 8 shows the EEG signal after the filtering process, in which the sinusoidal noise has been successfully removed.

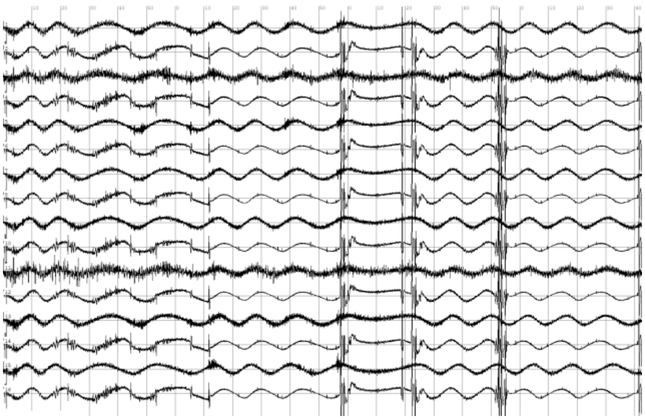

FIGURE 7. EEG Signal Plot Results After Decomposition Using ICA.

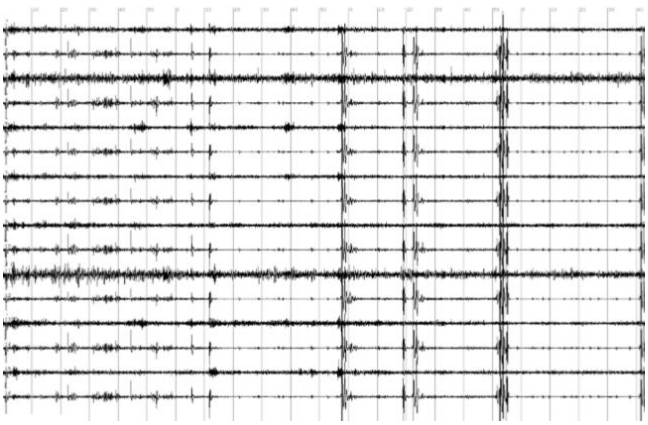

FIGURE 8. EEG signal plot results after filtering

C. TESTING SCENARIOS

Statistical analysis of p-values across all respondents in TABLE 2 reveals that certain features consistently have p-values below 0.05, indicating their significant contribution to class differentiation. Conversely, some features tend to have p-values above 0.05, suggesting they may introduce noise, which can negatively impact the model's performance. Therefore, feature selection is necessary to eliminate irrelevant or minimally contributing features. By reducing the number of insignificant features, the model can operate more efficiently and produce more accurate predictions [47]. However, the choice of feature selection method should be carefully considered. Although a feature may have a low p-value, indicating statistical significance, it does not necessarily mean it is crucial for prediction. Thus, a more comprehensive feature selection approach is needed to ensure an accurate and efficient model [48].

The classification of ERP on problematic gamers was done in three scenario. The first scenario involves testing the dataset without feature selection, using all 12 features as input data without any selection process for classifying "ERP Present" and "ERP Not Present." The second scenario involves testing the dataset with a metaheuristic algorithm for feature selection. In this scenario, the feature subset selected by the basic metaheuristic algorithm will serve as input for classification. The final scenario involves testing the implementation of a hybrid approach with the best metaheuristic algorithm from the second scenario, combined with B-SFS for feature selection prior to classification. The classification of "ERP" and "NO ERP" classes using this feature subset will be evaluated based on Accuracy, Specificity, and Sensitivity, using logistic regression and a voting classifier. Classification of ERP and non-ERP states is performed intra-subject, meaning that for each classification, only data from a single respondent is used. This approach is chosen because each individual exhibits different EEG signal patterns even when given the same stimulus [38], [39].

TABLE 2
p-value of each respondent's features

	PR 02	PR 04	PR 06	PR 07	PR 09
Mean	0.000**	0.001*	0.001*	0.000**	0.000**
Standard Deviation	0.000**	0.000**	0.000**	0.288	0.001*
Skewness	0.054	0.138	0.138	0.000**	0.001*
Kurtosis	0.135	0.766	0.766	0.691	0.676
Min	0.001*	0.073	0.073	0.589	0.773
Median	0.000**	0.073	0.073	0.000**	0.001*
Peak Latency	0.001*	0.459	0.459	0.222	0.478
Variance	0.001*	0.000**	0.000**	0.320	0.001*
Max Peak	0.000**	0.000**	0.000**	0.001*	0.000**
Power	0.001*	0.000**	0.000**	0.412	0.088
Hjorth Mobility	0.379	0.001*	0.001*	0.716	0.053
Hjorth Complexity	0.001*	0.228	0.000**	0.585	0.052

Note:
*** Significance at P < 0.05**
**** Significance at P < 0.001**

Based on the classification results across all subjects in TABLE 3 and TABLE 4, it can be concluded that both the Logistic Regression and Voting Classifier models generally achieved very high accuracy in classifying the data. However, not all models for each respondent achieved perfect performance, likely due to the presence of features that provide limited or irrelevant information. By removing irrelevant or minimally contributing features, the model can work more efficiently and produce more accurate predictions [40]. This can be achieved through feature selection. However, the choice of feature selection method should also be carefully considered, as traditional feature selection or manual feature removal based on feature values may result in less accurate and efficient predictive models [41].

Metaheuristic algorithms have emerged as a new standard in feature selection due to their ability to identify the best feature subset while consistently maintaining model accuracy [41]. These algorithms can identify optimal feature subsets from all possible combinations by evaluating each potential solution through a series of operations on the best solution [42]. In the second scenario, after the EEG signals undergo feature extraction, all features will go through a feature selection process using three metaheuristic algorithms: GA, PSO, and ACO. Each of these algorithms will generate a feature subset based on their respective search processes, as shown in TABLE 6. In the testing of this scenario, the use of metaheuristic algorithms successfully reduced the number of features used for classifying the "ERP Present" and "ERP Not Present" classes. This testing also resulted in improved classification performance for some respondents as shown in FIGURE 9 and FIGURE 10, demonstrating that the use of metaheuristic algorithms aligns with its goal of maximizing accuracy with minimal error [43]. The selection of feature subset combinations had an impact on the model's performance in classification, resulting in either an increase or decrease in performance. Almost all respondents saw an improvement in performance after using metaheuristics for feature selection, except for PR 07 and PR 09, which experienced a decrease in performance with the Voting Classifier. This suggests the need for a deeper search to find a more optimal combination of feature subsets. One approach to achieving this is by implementing algorithm hybridization, which combines two metaheuristics with a focus on more efficient and effective exploration and exploitation, to optimize the solution or feature subset and enhance the quality of the candidate solutions [43].

The testing of scenario three involves applying algorithm hybridization with the goal of finding a more optimal feature subset than the standard metaheuristic algorithms used in scenario two. The hybridization will be carried out by combining two metaheuristic algorithms: the best-performing metaheuristic algorithm for each respondent with the B-SFS algorithm. The best algorithm for each respondent will be selected based on the highest classification performance from the generated subset. In addition to performance, the algorithm that produces a smaller number of feature subsets will also be considered when selecting the best algorithm.

TABLE 3
Logistic Regression performance in scenario 1

	Accuracy	Sensitivity	Specificity
PR 02	0.98	1.00	0.95
PR 04	0.93	0.93	0.94
PR 06	1.00	1.00	1.00
PR 07	0.98	0.96	1.00
PR 09	0.98	1.00	0.96

TABLE 4
Voting Classifier performance in scenario 1

	Accuracy	Sensitivity	Specificity
PR 02	0.98	0.98	1.00
PR 04	0.98	0.98	1.00
PR 06	1.00	1.00	1.00
PR 07	0.98	0.96	1.00
PR 09	1.00	1.00	1.00

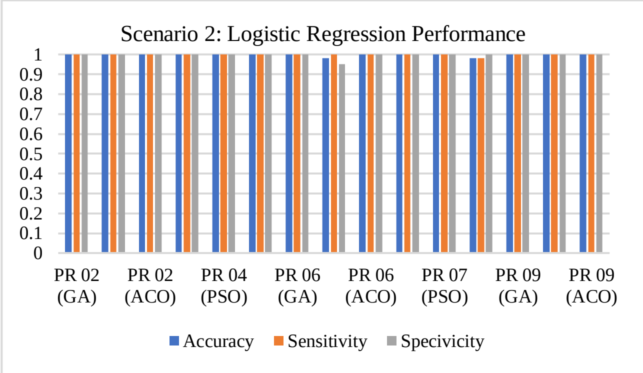

FIGURE 1. Logistic Regression performance using three metaheuristic algorithms in scenario 2

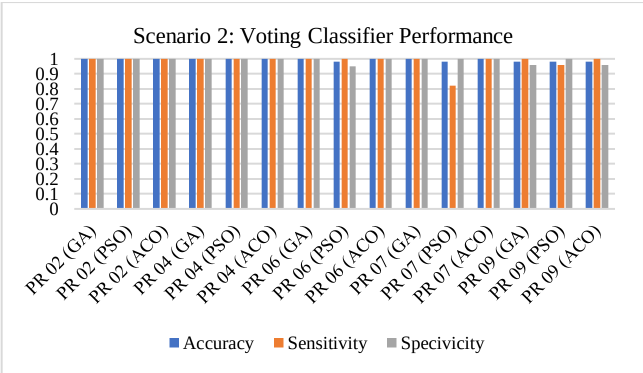

FIGURE 10. Voting Classifier performance using three metaheuristic algorithms in scenario 2

TABLE 5
Logistic Regression performance in scenario 3

	Accuracy	Sensitivity	Specificity
PR 02	1.00	1.00	1.00
PR 04	1.00	1.00	1.00
PR 06	1.00	1.00	1.00
PR 07	1.00	1.00	1.00
PR 09	1.00	1.00	1.00

TABLE 6
The results of the feature subsets selected by each metaheuristic algorithm in scenario 2

	PR 02			PR 04			PR 06			PR 07			PR 09		
	GA	PSO	ACO	GA	PSO	ACO	GA	PSO	ACO	GA	PSO	ACO	GA	PSO	ACO
Mean	✓			✓			✓	✓			✓		✓	✓	
Standard Deviation				✓							✓			✓	
Skewness	✓	✓						✓					✓		
Kurtosis	✓			✓			✓			✓	✓		✓		

Min	✓				✓			✓						✓	
Median		✓		✓	✓		✓	✓						✓	
Peak Latency				✓	✓		✓	✓					✓	✓	
Variance	✓				✓		✓	✓			✓		✓	✓	
Max Peak	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Power	✓	✓			✓			✓					✓	✓	✓
Hjorth Mobility		✓						✓		✓				✓	
Hjorth Complexity		✓				✓	✓	✓					✓	✓	
Fitness Value	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**

TABLE 7
Results of the subset of features selected by the hybrid metaheuristic and its comparison in scenario 3 against the conventional metaheuristic in scenario 2

	PR 02		PR 04		PR 06		PR 07		PR 09	
	ACO B-SFS	ACO	ACO B-SFS	ACO	GA B-SFS	GA	ACO B-SFS	ACO	ACO B-SFS	ACO
Mean						✓				
Standard Deviation	✓				✓		✓			
Skewness										
Kurtosis					✓	✓				
Min							✓			
Median					✓	✓				
Peak Latency						✓			✓	
Variance			✓			✓				
Max Peak	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Power	✓									✓
Hjorth Mobility					✓					
Hjorth Complexity			✓	✓	✓	✓				
Fitness Value	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**

TABLE 8
Voting Classifier performance in scenario 3

	Accuracy	Sensitivity	Specificity
PR 02	1.00	1.00	1.00
PR 04	1.00	1.00	1.00
PR 06	1.00	1.00	1.00
PR 07	1.00	1.00	1.00
PR 09	1.00	1.00	1.00

Based on TABLE 5 dan TABLE 8, the hybridization of the best algorithm from scenario two with B-SFS successfully demonstrated its ability to select optimal features and achieve perfect classification performance for all respondents. Implementing hybridization for feature selection in this scenario does not necessarily guarantee a reduction in the number of features; instead, it may result in an increase. Nonetheless, this hybridization still produces feature subsets with a minimal yet informative number of features. In this scenario, nearly all respondents experienced an increase in the number of features in their hybridized algorithm subset, except for respondent PR 06, who had one feature reduced in their subset as shown in TABLE 7.

V. DISCUSSION

The results reveal that Max Peak is a standout feature for each respondent, consistently selected by all algorithms in both scenario 2 and scenario 3, and it notably improves accuracy for most respondents. Its significant impact is evident when ACO, in scenario 2, selects Max Peak alone as the feature subset for respondents PR 02 and PR 07, achieving perfect classification performance. This selection is likely related to the ERP P300 characteristics, which can be detected by measuring amplitude during the largest spike at the positive voltage peak in the 200-500 ms range after the stimulus [22].

However, selecting Max Peak alone does not always guarantee improved performance, as seen with respondent PR 06 using ACO in scenario 2. Nevertheless, the combination of Max Peak and Kurtosis in the GA-generated subset for PR 06 in scenario 2 led to enhanced performance. The inclusion of Kurtosis indicates that the EEG signal from PR 06 may detect ERP by assessing the intensity of the tail distribution compared to the normal distribution tail [44]. The interaction of other features alongside Max Peak underscores the need for further exploration in searching for optimal feature subset combinations, prompting the use of metaheuristic hybridization with B-SFS.

Despite the hybrid metaheuristic's feature subset selection increasing the number of features for almost all respondents, it still resulted in perfect classification performance for every respondent. This highlights the effectiveness of B-SFS in the diffusion process, where the application of Gaussian distribution allows for an optimal solution search. This enables particles to move randomly around the best solution, thereby increasing the likelihood of finding more informative feature subsets [45].

TABLE 9
Previous studies

Reference	Scope/Case	Feature Selection	Results
[55]	IGD Classification	-	Accuracy:86.5%, Sensitivity: 89.3% Specificity: 83.3%.
[56]	IGD Classification	Filter Approach	Accuracy ranged from 63.5% to 73.1%
[57]	IGD Classification	-	Accuracy of Discriminant Analysis: 73%, SVM: 75%, Neural Network: 0.84
[58]	Classification of addiction levels in gaming	-	Accuracy: 63.3%

Based on TABLE 9, it can be observed that the classification model performance achieved in this study is superior to the results of previous studies that also focused on problematic gamers. This improvement can be attributed to the use of feature selection through metaheuristic and hybrid metaheuristic approaches. By leveraging algorithms such as Genetic Algorithm, Ant Colony Optimization, and Particle Swarm Optimization, combined with Binary Stochastic Fractal Search (B-SFS), the model is able to identify and select the most relevant and informative features. This approach reduces complexity and enhances accuracy, making feature selection through metaheuristics a crucial factor in improving the overall performance of the model in this study.

Despite the promising results, several limitations should be acknowledged. Validation of the hybrid metaheuristic's effectiveness has primarily been based on classification performance alone, without analyzing the importance values of each feature. As a result, this study does not fully explain the rationale behind how the hybrid metaheuristic selects its feature subsets. Future research could benefit from providing a more detailed explanation of the hybrid algorithm's operation, focusing on the features it selects and their significance.

Another limitation is that the study focuses solely on the group of problematic online gamers, without comparing the EEG signals to a control group. For example, it would be valuable to investigate whether problematic gamers exhibit more ERP responses when exposed to game stimuli compared to non-problematic gamers. Including such comparisons could provide deeper insights into how gaming behavior affects neural responses and help strengthen the findings by contrasting the two groups.

VI. CONCLUSION

This study successfully demonstrated the integration of EEG and ERP techniques combined with the GNAT to observe the neurophysiological responses of problematic online gamers to various stimulus themes. The hybrid approach involving metaheuristic algorithms (GA, ACO, PSO) and Binary Stochastic Fractal Search (B-SFS) achieved optimal performance in feature selection, with an accuracy, sensitivity, and specificity of 1.00 across all participants. The use of B-SFS significantly enhanced the identification of the most informative features related to problematic gaming behavior, emphasizing its effectiveness in EEG-based analysis. The findings suggest that advanced feature selection methods, such as B-SFS, could be applied in future research to monitor and intervene in problematic gaming behaviors. By improving the reliability of predictions based on neurophysiological indicators, these methods hold potential for developing intervention strategies and preventive measures for gaming addiction.

Future research could benefit from further exploration of the hybrid metaheuristic algorithm, with a detailed analysis of the selected features and their significance. Additionally, including control group comparisons would be valuable to investigate how problematic gamer’s ERP responses differ from those of non-problematic gamers when exposed to gaming stimuli. These comparisons could offer deeper insights into the neural impacts of gaming behavior and strengthen the findings. Furthermore, adding an ERP analysis related to impulsivity and responsiveness would be beneficial, as these components reflect an individual's tendency to respond and provide insights into the quality of their responses. Expanding the scope of these studies will contribute to a better understanding of how excessive gaming affects brain function and may pave the way for more effective interventions for gaming addiction.

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