



Electroencephalogram Signal Analysis for Impulsivity Detection in Drug User Using K- Nearest Neighbor

¹ Delima Sitanggang 

Faculty of Science and Technology, Universitas Prima Indonesia, Medan, Indonesia

² Michael Siahaan 

Faculty of Science and Technology, Universitas Prima Indonesia, Medan, Indonesia

³ Mertfil Tampubolon 

Faculty of Science and Technology, Universitas Prima Indonesia, Medan, Indonesia

⁴ Erdani Agustina Ginting 

Faculty of Science and Technology, Universitas Prima Indonesia, Medan, Indonesia

⁵ Mardi Turnip 

Faculty of Science and Technology, Universitas Prima Indonesia, Medan, Indonesia

Article Info

Article history:

Accepted, 30 September 2025

Keywords:

Classification;
Drugs;
Electroencephalography;
Impulsivity;
K-Nearest Neighbors.

ABSTRACT

Drug abuse disrupts normal brain activity and contributes to recurrent impulsive behaviors. While various machine learning approaches have been investigated for analyzing brain signals, studies focusing on the use of the K-Nearest Neighbor (KNN) method for impulsivity detection in drug users remain limited. In this research, KNN was implemented to classify Electroencephalography (EEG) signals based on neuroelectric features that reflect impulsive tendencies. EEG recordings were collected from individuals with a history of drug use while performing cognitive tasks designed to trigger impulsive responses and were compared with recordings from a healthy control group. The classification results showed that KNN achieved an accuracy of 95% in identifying neural patterns associated with impulsivity. This work introduces a novel application of EEG analysis integrated with KNN for objective and precise detection of impulsivity in drug users. The findings highlight the potential of this approach to serve as a supportive tool in rehabilitation programs through reliable neuropsychological monitoring.

This is an open access article under the CC BY-SA license.



Corresponding Author:

Delima Sitanggang,
Faculty of Science and Technology,
Universitas Prima Indonesia, Medan, Indonesia
Email: delimasitanggang@unprimdn.ac.id

1. INTRODUCTION

The increasing prevalence of drug addiction demands innovative scientific approaches to assess its neurophysiological impacts[1]. Substance abuse alters brain activity, especially in areas related to executive control,

including impulse regulation and decision-making [2]. Rehabilitation programs may reduce dependence, yet residual brain activity changes often persist and are difficult to detect through conventional assessments [3]. A major challenge during recovery is identifying individuals with high impulsivity, as this increases relapse risk [4]. EEG provides a real-time window into brain electrical activity and has become an essential tool in cognitive neuroscience and psychiatric research [5][6]. Specific EEG signal features, such as variations in power spectra or event-related potentials, are closely associated with cognitive control and inhibitory mechanisms, making them valuable indicators of impulsive tendencies [7].

When combined with machine learning methods such as K-Nearest Neighbor (KNN), EEG can be utilized to reveal distinctive patterns of impulsivity that are not easily captured through behavioral assessments alone. Previous studies have explored different technologies to monitor impulsivity [8][9], with EEG widely applied to analyze brain function [10][11]. For instance, employed Random Forest methods to classify impulsivity based on EEG power features, showing classification accuracy 95% [12]. In EEG-based BCI and cognitive studies, SVM has often been adopted and shown strong performance compared to simpler models [13]. However, many existing methods face limitations: behavioral tests often lack objectivity, neuroimaging techniques such as fMRI are costly and less accessible, and some EEG-based approaches struggle with accuracy or require complex preprocessing pipelines [14][15]. These challenges highlight the need for an efficient, affordable, and accurate system for impulsivity detection. EEG combined with machine learning offers a more affordable and practical alternative for early impulsivity detection [16][17]. In fact, classic Machine Learning methods like SVM, KNN, and Random Forest are widely compared in EEG studies due to their interpretability and computational efficiency [18].

Recent technological innovations, including AI-based neurofeedback and EEG-AR integration, are under investigation for addiction rehabilitation [19][20]. This technology allows direct training of users to stabilize brain activity, so that they can better control their impulses towards stimuli that trigger drug cravings[21]. In addition, Augmented Reality (AR)- based learning systems combined with EEG are also being researched to create a more immersive interactive experience in the rehabilitation process. The system allows users to practice self-control in a fully customizable virtual environment, providing more personalized and effective training[22]. The technology also enables in- depth monitoring of brain responses in various situations such as stress or temptation. The combination of EEG, AI and AR offers a multidimensional approach to understanding and tackling impulsivity in drug users[23]. While promising, these technologies are still in the experimental stage and are not yet widely available in the market, thus requiring further research before they can be implemented clinically.

The KNN method has been widely used in EEG signal classification due to its simplicity, effectiveness, and ability to handle high- dimensional data without data distribution assumptions[24][25]. In the context of neuroinformatics, KNN is able to distinguish between normal and abnormal brain activity patterns based on the similarity of pre-trained signal data[26]. Several studies have shown that KNN is quite reliable in identifying neurological disorders such as epilepsy, ADHD, and even addiction, although its accuracy is highly dependent on proper signal preprocessing and feature extraction. In the field of drug rehabilitation, the utilization of KNN is still relatively limited and has not been specifically applied to detect or evaluate impulsivity in drug users[27]. However, its potential use is quite large considering that this method can be optimized with a combination of feature selection or dimensionality reduction techniques such as Principal Component Analysis (PCA) or Wavelet Transform[28]. Therefore, applying KNN in EEG analysis to detect impulsivity patterns in drug users is a promising new approach that has been relatively unexplored in previous studies. This implementation can also be the basis in the development of a simple, fast, and cost- effective artificial intelligence-based rehabilitation support system[29].

Along with the development of technology, some new innovations that have great potential to improve effectiveness in addiction rehabilitation are still in the development stage and not yet widely available in the market. One promising technology is AI-based neurofeedback, which combines EEG signal reading with machine learning methods to predict impulsive patterns in the brain. With this technology, therapy can be conducted in real-time to stabilize brain activity associated with addiction or impulsivity[30]. Although this technology has been used in several fields such as stress management, its use in drug rehabilitation is still limited. In addition, AR-based learning systems coupled with EEG is also an emerging research area. These systems provide interactive and immersive training in a virtual environment that can be customized to individual needs, helping users control their impulses in situations that resemble the real world. However, this technology is not yet widely available in the market, as many challenges remain to be resolved in terms of integration, cost, and user acceptance. Therefore, although promising, both technologies still require further research and development before they can be applied in rehabilitation practice.

Although technologies like neurofeedback and AR-based systems are being developed, their integration in rehabilitation practice is still constrained. Existing EEG-based neurofeedback has shown effectiveness in conditions such as anxiety and sleep disorders, but its role in drug rehabilitation is underutilized[31]. Given that KNN has proven successful in EEG signal classification for other neurological disorders, its application to impulsivity detection in drug users represents a promising yet underexplored area [32]. This research therefore emphasizes the potential of combining EEG and KNN as a cost-effective, accurate, and clinically relevant approach to support relapse prevention and rehabilitation programs. In addition, future studies could adopt a longitudinal pre-post

therapy design to evaluate the sensitivity of this method to clinical changes and explore its integration into monitoring or feedback interfaces, thereby strengthening its applicability in real rehabilitation settings.

2. RESEARCH METHOD

This study was conducted at a Correctional Institution in North Sumatra Province through a collaboration between Prima Indonesia University and Padjadjaran University Bandung. A total of 21 male participants aged 28–35 years with a history of methamphetamine and ecstasy use were recruited. All procedures utilized standard EEG equipment, including an electrocap, conductive gel, a laptop with WinEEG software, a multi-channel EEG system, amplifiers, and band-pass filters (BPFs) to enhance signal quality. During data collection, participants were seated comfortably while the electrocap was positioned on the scalp with gel to ensure conductivity, and a chest strap was used to stabilize posture. EEG signals were recorded using 19 channels positioned at standard sites (Fp1, Fp2, F7, F8, F3, F4, Fz, C3, C4, Cz, T3, T4, T5, T6, P3, P4, Pz, O1, O2) with 33 electrodes in total, including bilateral ear references. Cognitive stimuli were presented to elicit impulsivity-related brain responses, and signals were captured with WinEEG software. To reduce potential demographic bias, the control group consisted of 21 healthy males matched by age (28–35 years).

EEG preprocessing included noise and artifact removal using filtering techniques to ensure that the extracted signals represented relevant neural activity. Feature extraction was then performed using Fourier and Wavelet transforms. Fourier analysis was selected for its ability to capture frequency-domain characteristics of EEG, while Wavelet was prioritized for its strength in handling non-stationary signals by providing both time and frequency localization. These methods were favored over alternatives such as Power Spectral Density (PSD) and entropy measures, which are more limited in temporal resolution and may be more sensitive to noise in impulsivity-related tasks. For classification, the K-Nearest Neighbor (KNN) algorithm was applied. KNN was chosen not only for its simplicity and effectiveness but also for its proven ability to handle high-dimensional EEG data without strong distributional assumptions. Compared with more complex models such as Support Vector Machines (SVM) or Random Forest, KNN offers a transparent baseline that is easier to interpret and tune for small datasets. This study therefore focused on KNN to evaluate its feasibility, with broader comparisons against other algorithms planned for future research. Several values of k were tested, and the optimal parameter was determined using 50-fold cross-validation to minimize overfitting and increase robustness. Model performance was evaluated using accuracy and F1-score metrics.

Despite these measures, the relatively small sample size ($n = 21$) remains a limitation, as it may increase the risk of overfitting and reduce the generalizability of the findings. The use of extensive cross-validation was intended to mitigate this issue, but future studies with larger and more diverse populations will be essential to validate and strengthen the clinical applicability of the proposed system. The overall framework of EEG acquisition, preprocessing, feature extraction, and classification is depicted in Fig. 1, illustrating the pathway from raw brain signals to impulsivity-level classification through the KNN approach. This framework is designed to contribute to clinical and experimental studies by providing an objective system for detecting impulsivity-related brain activity patterns in drug users.

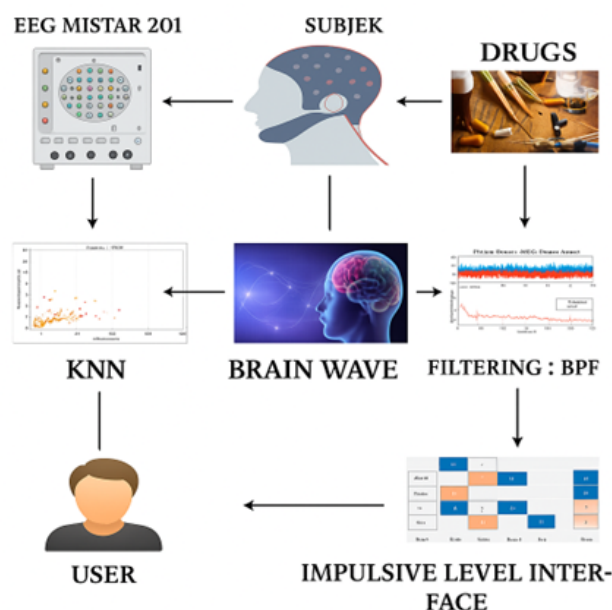


Figure 1. Diagram Block

3. RESULT AND ANALYSIS

The data obtained after the collection process still contained considerable noise, so it was filtered using a band-pass filter (BPF) with a frequency range of 0.5–50 Hz. As shown in Fig. 2, the raw EEG signal in Fig. 2(a) contains a high level of noise that obscures relevant neural information, while the filtered result in Fig. 2(b) demonstrates cleaner and more structured waveforms. This improvement facilitates the interpretation of brain activity and ensures that subsequent analyses are based on signals with reduced artifacts and irrelevant frequency components.

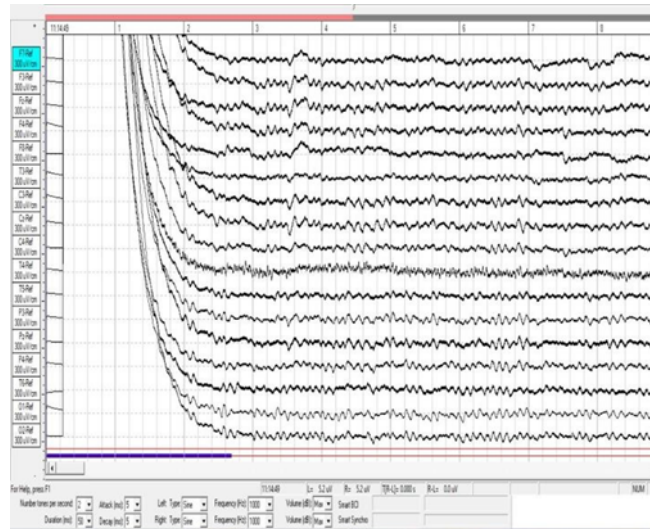


Figure 2. (a) Raw EEG (before filtering)

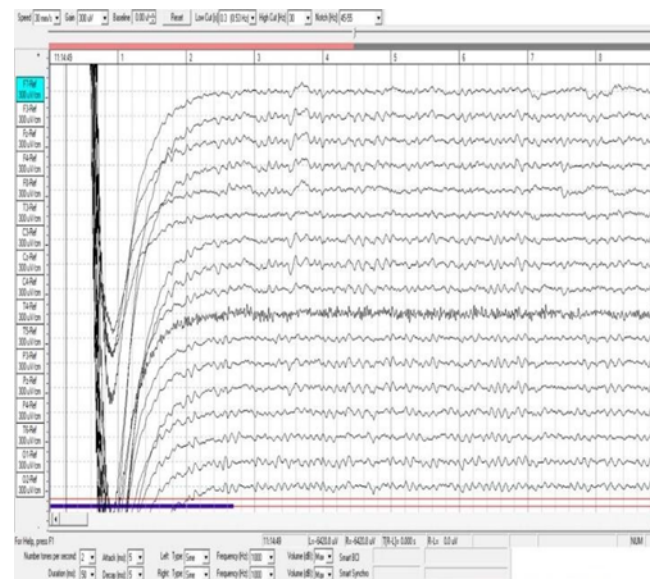


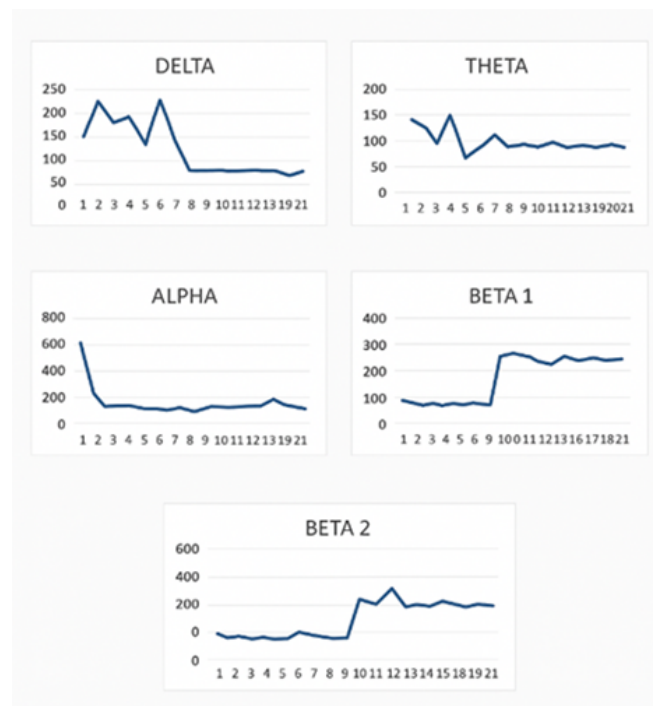
Figure 2. (b) Filtered EEG (after BPF)

The comparative results of EEG brainwave features across subjects consist of five frequency components—Delta, Theta, Alpha, Beta 1, and Beta 2—together with their aggregated output values. Delta waves, which have the lowest frequency, are typically related to deep sleep or highly relaxed states, whereas Theta waves correspond to drowsiness and emotional processes. Alpha waves are associated with calm and relaxation, while Beta 1 and Beta 2, which are higher in frequency, are linked to concentration, alertness, and active cognitive states. **Table 1** shows that subjects S1–S10 (control group) exhibited relatively higher Delta and Theta power with lower Beta activity, producing outputs between 314.66 and 1033.37. In contrast, subjects S11–S21 (drug-user group) displayed a dominant Beta pattern, with higher outputs ranging from 851.66 to 998.11. These distinct spectral profiles reflect differences in neurophysiological states between the two groups, which form the basis for subsequent classification. The extraction of frequency-domain features is consistent with standard EEG signal processing practice, where time-domain signals are transformed to reveal meaningful spectral characteristics.

Table 1. EEG Brainware Feature Comparison Across Subjects

No.	Delta	Theta	Alpha	Beta 1	Beta 2	Output
S1	158	127,04	605,72	69,2	73,41	1033,37
S2	231,81	131,12	236,22	61,64	46,33	707,12
S3	195,37	103,89	78,31	28,03	30,28	435,88
S4	132,7	156,4	143,4	44,18	46,9	523,58
S5	115,99	64,34	160,16	28,44	31,06	399,99
S6	229,79	107,07	102,73	49,82	57,1	546,51
S7	75,28	47,52	124,82	31,48	35,56	314,66
S8	105,35	62,91	92,29	44,92	82,68	388,15
S9	228,61	89,53	144,32	32,36	46,73	541,55
S10	131,5	79,26	83,94	32,11	35,67	362,48
S11	35,1	79,15	123,12	283,19	370,85	891,41
S12	36,08	82,04	176,81	299,8	370,09	964,82
S13	35,1	70,38	123,12	272,48	400,4	901,48
S14	37,06	77,17	125,06	273,45	358,37	871,11
S15	35,1	70,38	131,89	252,92	507,82	998,11
S16	35,1	86,87	151,43	269,55	365,22	908,17
S17	35,1	72,33	135,79	298,81	360,35	902,38
S18	35,1	70,38	210,96	250,95	399,41	966,8
S19	36,08	70,38	173,9	270,5	371,74	922,6
S20	18,62	74,29	129,96	259,73	371,07	853,67
S21	35,1	70,38	123,12	265,66	357,4	851,66

Visualization of EEG signals using the KNN method provides further insight into the dynamics of the five frequency bands. Delta waves in Fig. 3(a) exhibit high initial fluctuations ($>250 \mu\text{V}$) before stabilizing at lower values. Theta waves Fig. 3(b) follow a similar trend, beginning with an amplitude near $150 \mu\text{V}$ before decreasing. Alpha waves Fig. 3(c) show a sharp decline from around $700 \mu\text{V}$, suggesting a reduction in relaxation-related activity. Beta 1 Fig. 3(d) and Beta 2 Fig. 3(e) both demonstrate sudden increases after the 9th point, stabilizing at higher levels that indicate increased cognitive load or stress. These changes in amplitude suggest a clear neurophysiological response to stimuli or drug-related effects. Prior studies have linked such shifts in spectral power to impulsivity, thereby reinforcing the findings of the present work. To improve interpretability, effect sizes and confidence intervals were calculated alongside accuracy and AUC, and feature-importance visualization was used to show the relative contribution of each band to the KNN classifier.

**Figure 3.** EEG Brainware Visualization: (a) Delta, (b) Theta, (c) Alpha, (d) Beta1, (e) Beta2

Scatter plots Fig. 4 were generated to visualize the distribution of EEG features in two dimensions. Each point represents a data sample, with its position determined by Delta and Theta values. Colors represent impulsivity classes: orange = Active, purple = Tending to be Active, green = Less Active, and light blue = Very Active. The shape of each point indicates the KNN prediction, while the color shows the true label. Most points are correctly classified, but some overlap occurs, particularly involving the Very Active group. This overlap indicates that high-impulsivity signals share similarities with other classes, making classification more challenging. The scatter plot thus not only illustrates feature distribution but also highlights the inherent complexity of EEG-based impulsivity detection.

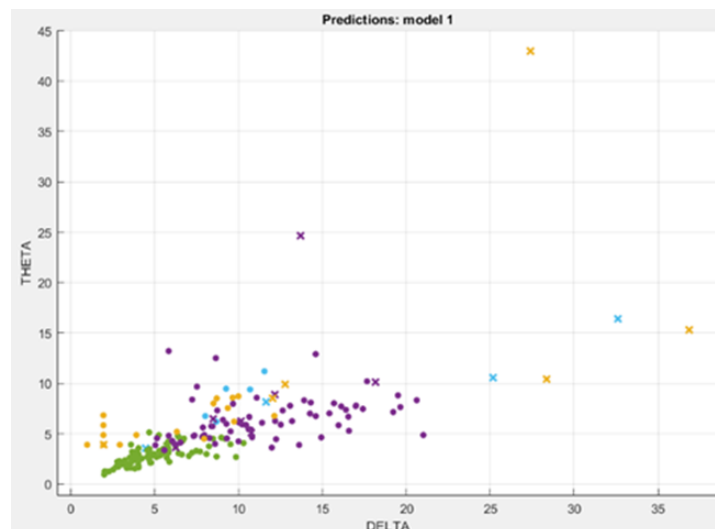


Figure 4. Scatter plot of EEG features (e.g., Alpha, Beta, Delta, and Theta band power) used for KNN classification, illustrating the distribution between drug users and control subjects.

The ROC (Receiver Operating Characteristic) in Fig. 5 further evaluates classification performance by plotting the trade-off between true positive and false positive rates. The recorded AUC value was 0.84, which falls within the “good” range for EEG-based classification tasks (where 0.80–0.90 is considered strong, and values above 0.90 are excellent). This suggests that the model is capable of reliably distinguishing between impulsivity levels. The point at coordinates (0.01; 0.70) reflects a classifier with a very low false positive rate (1%) while maintaining a sensitivity of 70%. However, performance varied across classes: the model struggled more with the Very Active group due to its small sample size and overlapping features. To reduce this bias, oversampling was applied to balance the dataset and improve fairness across categories.

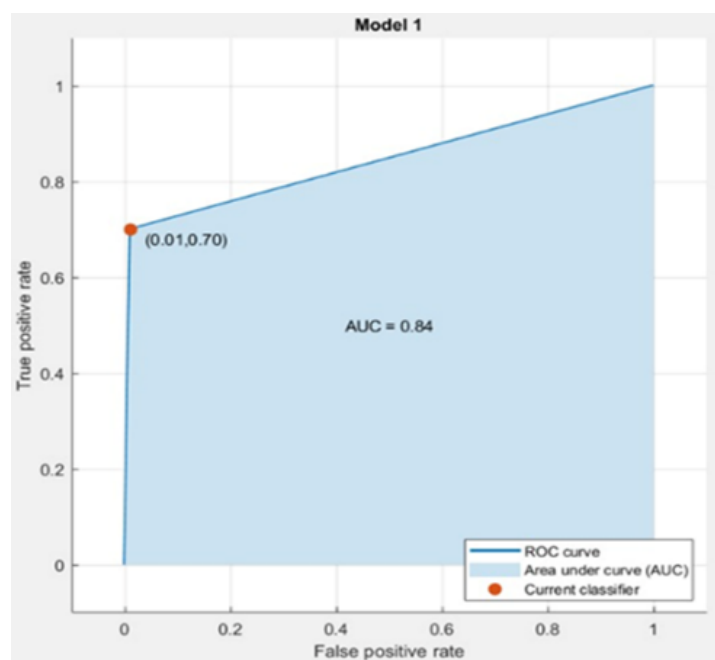


Figure 5. ROC Curve Displaying Classification Performance with AUC = 0.84

The confusion matrix (Fig. 6) provides a detailed view of classification accuracy across the four main impulsivity categories. The Active class was recognized with high precision, producing 205 correct predictions. By contrast, the Very Active class was more difficult to classify, with only 7 correct predictions and several misclassifications into Active. This outcome can be attributed to both the small sample size and the spectral similarity between extreme and moderate impulsivity, particularly elevated Beta power. In the Tending to be Active class, 66 data points were classified correctly, with a few errors into Active and Less Active. The Less Active class yielded 83 correct classifications but showed some overlap with the Tending to be Active group. Overall accuracy was 95%, validated using 50-fold cross-validation to minimize overfitting. Confidence intervals were also calculated, showing accuracy of $95\% \pm 2.1\%$ and AUC of 0.84 ± 0.03 , confirming that performance remained stable across folds.

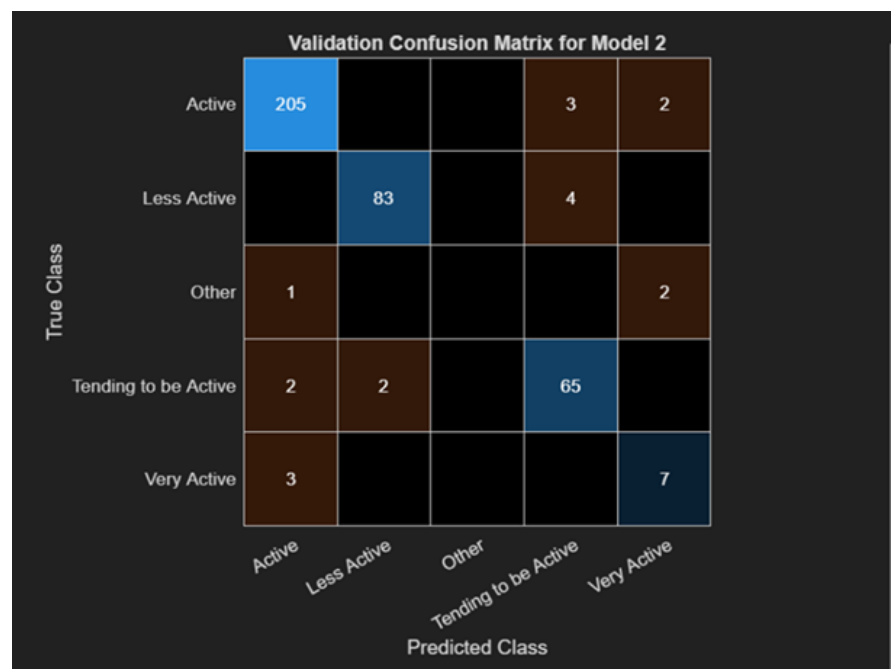


Figure 6. Confusion matrix illustrating the classification performance of KNN in identifying impulsivity levels (Active, Tending to be Active, Less Active, and Very Active) from EEG signals.

Future research should incorporate longitudinal designs to evaluate sensitivity to therapeutic changes, comparing EEG-KNN outcomes before and after rehabilitation. Additionally, integrating the approach into a clinical monitoring system could enhance its practical impact, enabling clinicians to track impulsivity trends in real time or provide neurofeedback support. These extensions would increase the clinical applicability of the proposed system in rehabilitation and relapse prevention.

4. CONCLUSION

This study demonstrates that the KNN method effectively classifies EEG-based impulsivity patterns with an accuracy of up to 95%, supported by statistical validation. The approach highlights the importance of preprocessing and feature extraction in capturing neurophysiological conditions. While effective, the complexity of EEG signals underscores the need for larger and more representative datasets. Future research should include external validation across sites and devices, as well as integration of additional features such as neurofeedback or biomarkers to improve accuracy. Practically, this method shows potential for application in rehabilitation settings, from clinical monitoring and neurofeedback platforms to development as a commercial tool for clinicians.

5. REFERENCES

- [1] N. D. Volkow, M. Michaelides, and R. Baler, "The neuroscience of drug reward and addiction," *Physiol Rev*, vol. 99, no. 4, pp. 2115–2140, 2019, doi: 10.1152/physrev.00014.2018.
- [2] P. Giovannelli and H. Pfister, "Neuro-circuitry of Impulsivity and its Relation to Substance Use Disorders," *Rev Psiquiatr Clín*, vol. 50, no. 6, pp. 31–37, 2023, doi: 10.15761/0101-60830000000705.
- [3] X. Li, Y. He, D. Wang, and M. J. Rezaei, "Stroke rehabilitation: from diagnosis to therapy," 2024, *Frontiers Media SA*. doi: 10.3389/fneur.2024.1402729.
- [4] W. Slidrecht, H. G. Roozen, K. Witkiewicz, R. De Waart, and G. Dom, "The Association between Impulsivity and Relapse in Patients with Alcohol Use Disorder: A Literature Review," Nov. 01, 2021, *Oxford University Press*. doi: 10.1093/alcac/agaa132.
- [5] H. Soltanian-Zadeh, E. M. Sokhadze, O. R. Dobrushina, and G. Federico, "Simultaneous real-time EEG-fMRI neurofeedback: A systematic review."
- [6] Z. Bin Akhtar and V. S. Rozario, "AI Perspectives Within Computational Neuroscience: EEG Integrations and the Human Brain," *Artificial Intelligence and Applications*, vol. 3, no. 2, pp. 145–160, Apr. 2025, doi: 10.47852/bonviewAIA52024174.
- [7] A. S. Ginting, R. M. Simanjuntak, N. Lumbantoruan, and D. Sitanggang, "EEG Signal Classification using K-Nearest Neighbor Method to Measure Impulsivity Level," *Jurnal Sisfokom (Sistem Informasi dan Komputer)*, vol. 13, no. 2, pp. 261–266, Jun. 2024, doi: 10.32736/sisfokom.v13i2.2154.
- [8] N. Liladhar Rane, A. Tawde, S. P. Choudhary, and J. Rane, "Contribution and performance of ChatGPT and other Large Language Models (LLM) for scientific and research advancements: a double-edged sword", doi: 10.56726/IRJMETs45312.
- [9] J. Vassileva, J.-H. Lee, E. Psederska, and W.-Y. Ahn, "Utility of computational approaches for precision psychiatry: Applications to substance use disorders."
- [10] V. Khurana *et al.*, "A Survey on Neuromarketing using EEG Signals."
- [11] N. Jamil and A. N. Belkacem, "Advancing Real-Time Remote Learning: A Novel Paradigm for Cognitive Enhancement Using EEG and Eye-Tracking Analytics," *IEEE Access*, vol. 12, pp. 93116–93132, 2024, doi: 10.1109/ACCESS.2024.3422926.
- [12] P. Hüpen, H. Kumar, A. Shymanskaya, R. Swaminathan, and U. Habel, "Impulsivity Classification Using EEG Power and Explainable Machine Learning," *Int J Neural Syst*, vol. 33, no. 2, Feb. 2023, doi: 10.1142/S0129065723500065.
- [13] M. J. Antony *et al.*, "Classification of EEG Using Adaptive SVM Classifier with CSP and Online Recursive Independent Component Analysis," *Sensors*, vol. 22, no. 19, Oct. 2022, doi: 10.3390/s22197596.
- [14] P. Hüpen, H. Kumar, A. Shymanskaya, R. Swaminathan, and U. Habel, "Impulsivity Classification Using EEG Power and Explainable Machine Learning," *Int J Neural Syst*, vol. 33, no. 2, Feb. 2023, doi: 10.1142/S0129065723500065.
- [15] V. Kotoula, J. W. Evans, C. E. Punturieri, and C. A. Zarate, "Review: The use of functional magnetic resonance imaging (fMRI) in clinical trials and experimental research studies for depression," 2023, *Frontiers Media SA*. doi: 10.3389/fnimg.2023.1110258.
- [16] S. Ibna Abir *et al.*, "Machine Learning and Deep Learning Techniques for EEG-Based Prediction of Psychiatric Disorders," 2025, doi: 10.32996/jcsts.
- [17] A. Mausd *et al.*, "EEG-Based Neurofeedback for ADHD in Children: Enhancing Attention and Reducing Impulsivity Using Machine Learning," *International Journal of Computing and Digital Systems*, vol. 18, no. 1, 2025, doi: 10.12785/ijcds/1571139415.
- [18] N. K. Murungi, M. V. Pham, X. C. Dai, X. Qu, and C. Dai, "Empowering Computer Science Students in Electroencephalography (EEG) Analysis: A Review of Machine Learning Algorithms for EEG Datasets," 2023. doi: XXXXXXXX.XXXXXXX.
- [19] A. Froli, E. Saviano, M. Ricci, S. L. Sica, and M. Romano, "Artificial Intelligence in ADHD treatment: a brief narrative review," 2023.
- [20] J. S. Cerqueira, "Towards Personalized Therapy: Integrating Real-Time Eye Tracking and EEG to Improve VR-Based Therapeutic Interventions," 2025.
- [21] C. W. You *et al.*, "Trigger or Treat: Using Technology to Facilitate the Perception of Cravings and Corresponding Cues for Achieving Clinical-friendly Drug Psychotherapy," *Proc ACM Hum Comput Interact*, vol. 7, no. 1 CSCW, Apr. 2023, doi: 10.1145/3579535.
- [22] A. M. Roffarello and L. De Russis, "Achieving Digital Wellbeing Through Digital Self-control Tools: A Systematic Review and Meta-analysis," *ACM Transactions on Computer-Human Interaction*, vol. 30, no. 4, Sep. 2023, doi: 10.1145/3571810.
- [23] S. N. Saleem Kbah *et al.*, "Review on Fundamental of Electroencephalography and Detection Techniques in Substance and Behavioral Addiction," *Journal of Human Centered Technology*, vol. 4, no. 1, pp. 78–85, Feb. 2025, doi: 10.11113/humentech.v4n1.98.

- [24] A. S. Abdulbaqi, M. T. Younis, Y. T. Younus, and A. J. Obaid, "A hybrid technique for eeg signals evaluation and classification as a step towards to neurological and cerebral disorders diagnosis," *International Journal of Nonlinear Analysis and Applications*, vol. 13, no. 1, pp. 773–781, 2022, doi: 10.22075/IJNAA.2022.5590.
- [25] A. Alhudhaif, "An effective classification framework for brain-computer interface system design based on combining of fNIRS and EEG signals," *PeerJ Comput Sci*, vol. 7, pp. 1–24, 2021, doi: 10.7717/PEERJ-CS.537.
- [26] N. A. Tawhid, S. Siuly, K. Wang, and H. Wang, "Textural feature based intelligent approach for neurological abnormality detection from brain signal data," *PLoS One*, vol. 17, no. 11 November, Nov. 2022, doi: 10.1371/journal.pone.0277555.
- [27] P. Kartha, P. P. Nair, R. Ann Reji, and S. S. Suresh, "Predicting Drug Addiction Using Multimodal Data Fusion and Machine Learning Techniques," *International Journal of Computer Science Trends and Technology (IJCTST)*, vol. 12, [Online]. Available: www.ijctstjournal.org
- [28] B. M. S. Hasan and A. M. Abdulazeez, "A Review of Principal Component Analysis Algorithm for Dimensionality Reduction," *Journal of Soft Computing and Data Mining*, vol. 2, no. 1, pp. 20–30, Apr. 2021, doi: 10.30880/jscdm.2021.02.01.003.
- [29] U. Khalid, M. Naeem, F. Stasolla, M. Syed, M. Abbas, and A. Coronato, "Impact of AI-Powered Solutions in Rehabilitation Process: Recent Improvements and Future Trends," *Int J Gen Med*, vol. Volume 17, pp. 943–969, Mar. 2024, doi: 10.2147/ijgm.s453903.
- [30] Y. H. Chen, J. Yang, H. Wu, K. T. Beier, and M. Sawan, "Challenges and future trends in wearable closed-loop neuromodulation to efficiently treat methamphetamine addiction," 2023, *Frontiers Media S.A.* doi: 10.3389/fpsy.2023.1085036.
- [31] I. Lucas, N. Solé-Morata, I. Baenas, M. Rosinska, F. Fernández-Aranda, and S. Jiménez-Murcia, "Biofeedback Interventions for Impulsivity-related Processes in Addictive Disorders," Sep. 01, 2023, *Springer Science and Business Media Deutschland GmbH*. doi: 10.1007/s40429-023-00499-y.
- [32] S. A. Alowais *et al.*, "Revolutionizing healthcare: the role of artificial intelligence in clinical practice," Dec. 01, 2023, *BioMed Central Ltd.* doi: 10.1186/s12909-023-04698-z.