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Analysis of brain activity to methamphetamine stimulus using electroencephalography technology with Naive Bayes algorithm

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ABSTRACT

The increasing use of methamphetamine among young generations has led to significant alterations in brain function, affecting both behavior and mental health. However, scientific understanding of the neural activity changes induced by methamphetamine remains limited. This study aims to analyze brainwave patterns using electroencephalography (EEG) and classify addiction response levels through the Naive Bayes algorithm. The experimental procedure involved presenting each subject with visual stimuli related to methamphetamine while recording their brain activity using EEG for three minutes. The extracted EEG features were then analyzed with the Naive Bayes classifier. The results demonstrated a classification accuracy of 97.9%. The proposed method successfully categorized brain activity patterns into five levels of response: non-addicted, mildly addicted, moderately active, addicted, and highly addicted. These findings indicate that the Naive Bayes algorithm is effective in distinguishing subtle variations in brainwave patterns associated with different levels of methamphetamine addiction response.

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1. INTRODUCTION

The increasing prevalence of methamphetamine use, particularly among younger populations, has raised serious concerns due to its harmful effects on brain function, cognition, and mental health [1]. Drug abuse continues to spread worldwide with proven negative consequences, both material and non-material, and in some cases even leading to death [2]. Therefore, individuals suffering from addiction require immediate cessation and recovery efforts [3]. At present, technologies for early detection of drug use remain limited and demand further development. Commonly used methods, such as urine tests, are often conducted randomly and lack comprehensiveness, allowing some drug users to go undetected [4], [5]. One promising technology for detection is electroencephalography (EEG), a non-invasive tool capable of recording brain electrical activity in real time, which has been widely applied in pharmaco-EEG to evaluate the neural effects of psychoactive substances [6].

Despite its advantages, EEG data are inherently complex and require advanced analytical methods to extract meaningful information. One of the most widely studied EEG components in the context of psychoactive substance effects is the P300 wave, which is closely associated with cognitive processes such as attention and decision-making [7]. Alterations in P300 amplitude or latency have been reported as indicators of cognitive impairment caused by methamphetamine use. To maximize the potential of EEG as an early detection tool, it is essential to integrate it with intelligent computational approaches such as machine learning algorithms [8]. Among classification algorithms, Naive Bayes stands out for its ability to efficiently identify brainwave patterns with relatively small training datasets, effectively handle high-dimensional feature spaces, and maintain robustness in the presence of noisy data [9].

Other diagnostic methods, including urine, blood, hair, and saliva testing are commonly used to detect methamphetamine consumption; however, each comes with limitations in terms of detection windows [10], [11]. In contrast, prior studies have highlighted the significant potential of EEG as a biomarker for assessing dependence severity, as spectral alterations are consistently observed among drug user groups [12]. For instance, methamphetamine abusers have been shown to exhibit increased gamma power and disrupted connectivity in EEG recordings, correlating with craving intensity and cognitive decline [13]. Recent advances in machine learning further demonstrate the feasibility of integrating EEG features with classifiers such as bidirectional long short-term memory (BiLSTM) and support vector machine (SVM) to differentiate methamphetamine users from healthy controls [14]. Nevertheless, research specifically addressing EEG responses to methamphetamine stimuli remains limited, particularly regarding integration with probabilistic classifiers such as Naive Bayes.

Naive Bayes, a probabilistic classification algorithm based on Bayes' Theorem with the assumption of feature independence, offers advantages including computational efficiency, low storage requirements, and resistance to overfitting. Previous studies have demonstrated its effectiveness, such as in EEG analysis for children with fetal alcohol syndrome and in classifying EEG signals from individuals with alcohol dependence, where its performance was competitive compared to other algorithms [15], [16]. Based on this background, the present study aims to analyze brain activity in response to methamphetamine stimuli using EEG technology and apply machine learning algorithms for response classification. This study was conducted in accordance with the ethical principles outlined in the Declaration of Helsinki. Prior to data collection, all participants received a comprehensive explanation of the study objectives, procedures, potential risks, and their right to withdraw at any time. Participation was confirmed through verbal consent, and all data were anonymized and securely stored in compliance with applicable guidelines.

2. METHOD

This study was conducted at one of the correctional institutions in North Sumatra, in collaboration with Universitas Prima Indonesia and Universitas Padjadjaran Bandung. EEG recordings were acquired using WinEEG software, a Mitsar 201 amplifier, Electro Cap, and Electro Gel as the conductor [17]. The EEG amplifier served to enhance weak brain electrical signals, enabling high-accuracy recordings. This configuration allowed real-time monitoring of brainwave changes and observation of neurological dynamics in response to the stimuli [18]. A total of 21 participants aged 20–30 years old were included in the study. Inclusion criteria required participants to have the ability to provide informed consent, and full consciousness during EEG acquisition. Exclusion criteria included a history of epilepsy or other major neurological disorders, and the current use of sedative medication. During the experiment, subjects were seated comfortably in front of a monitor in a relaxed condition. Brain activity was recorded for three minutes while participants were exposed to visual stimuli related to methamphetamine. EEG signals were obtained using 19 electrodes placed according to the International 10–20 system: Fp1, Fp2, F7, F3, Fz, F4, F8, T3, C3, Cz, C4, T4, T5, P3, Pz, P4, T6, O1, and O2, with reference electrodes A1 and A2 positioned on the earlobes [19]. Recordings were performed at a sampling frequency of 128 Hz using Ag/AgCl-based electrodes, with signal amplification and low-noise circuitry to maintain data quality. The experiment was conducted in a soundproof room with controlled lighting, and the stimulus exposure lasted for three minutes.

EEG signals underwent a comprehensive preprocessing pipeline to improve data quality. A 12 Hz band-pass filter was applied to attenuate noise while preserving relevant frequency components (delta, theta, alpha, beta, and gamma). Artifact correction was subsequently performed, with a focus on electrooculogram (EOG) interference using regression- or component-based methods. Spectral analysis was then conducted to estimate power distribution across frequency bands, followed by independent component analysis (ICA) to further suppress residual artifacts [20]. Finally, z-score normalization was applied to ensure inter-channel and inter-subject comparability, allowing extracted features to represent neural dynamics rather than absolute amplitude variations. Feature extraction was a crucial step, as it determined the quality of the data used in classification [21]. The experimental setup is illustrated in Figure 1, which shows the EEG device, electrode placement, and the data acquisition workflow. Classification was primarily performed using the Naive Bayes algorithm due to its simplicity, computational efficiency, and capability of handling high-dimensional data with limited samples. For benchmarking purposes, additional models such as SVM and k-Nearest Neighbor (k-NN) were also applied. All models were implemented in MATLAB with default parameters. Model evaluation was conducted using 5-fold cross-validation, where the dataset was divided into five equal subsets, with each subset serving once as the test data while the remaining four were used as training data. The average accuracy across the five iterations was calculated to provide a more stable performance estimate [22]. Evaluation metrics included accuracy, precision, recall, F1-score, and the confusion matrix. A one-sample t-test was performed to compare the mean EEG output following methamphetamine stimulus with a reference value serving as a baseline. The purpose was to determine whether the observed mean differed significantly from the baseline, indicating a real effect of the stimulus on brain activity.

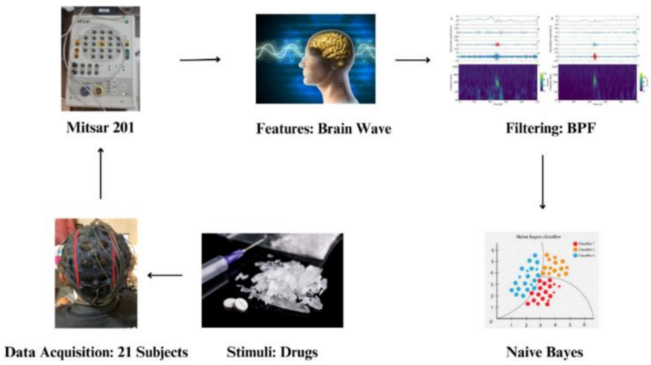


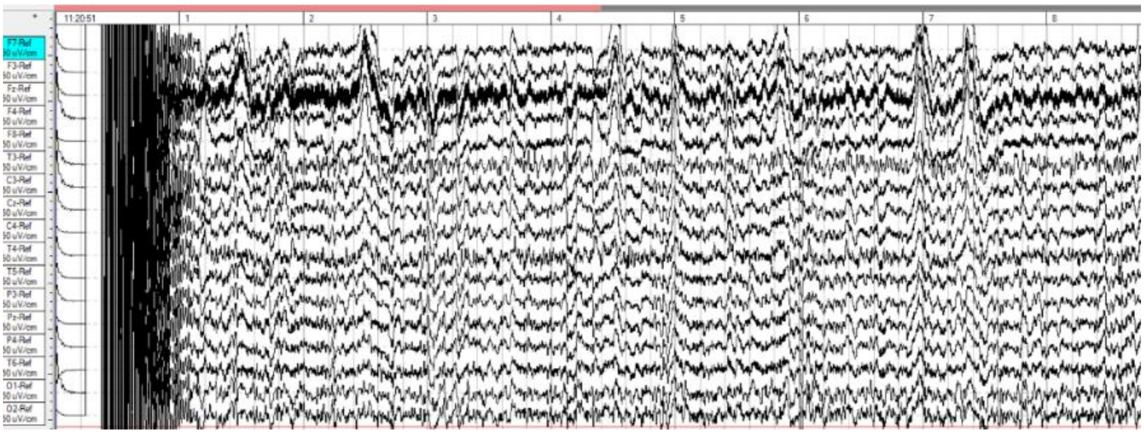
Figure 1. Block diagram

3. RESULTS AND DISCUSSION

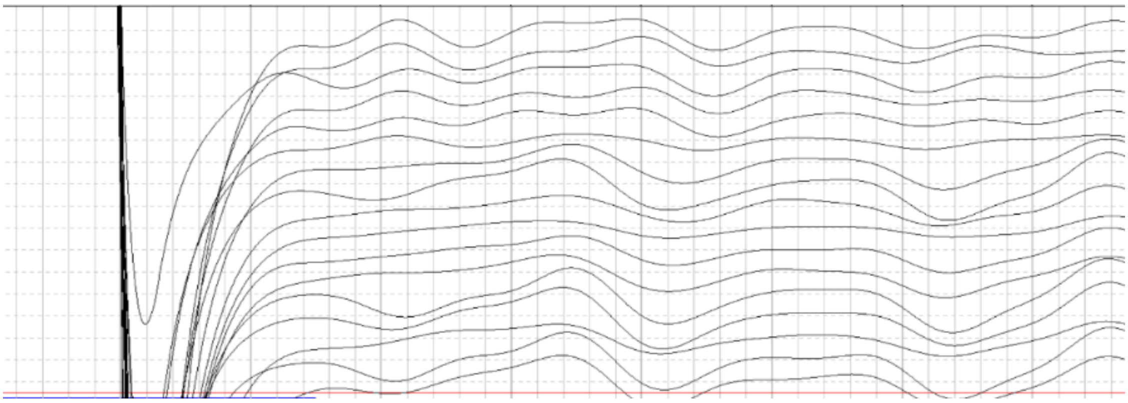
Figure 2 presents the representation of the EEG signals used in this study to analyze brain activity in response to stimuli. The figure illustrates the transformation of EEG data from its original recorded form into a processed signal suitable for further analysis. Figure 2(a) shows the raw EEG signals recorded from multiple channels, where the waveforms appear complex and contain various artifacts and noise, particularly at the beginning of the recording as indicated by high-amplitude fluctuations. In contrast, Figure 2(b) displays the EEG signals after preprocessing, including filtering and normalization steps. The resulting waveforms are smoother and more structured. The analysis of brain activity in response to methamphetamine stimuli using EEG revealed significant changes in brain wave patterns. An increase in beta and gamma wave activity following the stimulus reflected heightened alertness and neural hyperactivity, consistent with the psychostimulant effects of the substance. The preprocessing was shown to improve EEG signal quality by reducing noise and removing artifacts, particularly EOG signals [23]. Spectral analysis revealed different power distributions across various frequency bands (delta, theta, alpha, beta, and gamma) after subjects received methamphetamine stimuli. The most notable changes were observed in the increased power of beta and gamma waves, which are associated with cognitive activity and neurological stress responses. This improvement demonstrates that preprocessing plays a crucial role in enhancing signal clarity and supporting more reliable analysis in EEG-based studies.

Table 1 presents the results of feature extraction from EEG signals across different brain wave types. By observing the variations in dominant waveforms, researchers can obtain valuable insights into the mental states and activity levels of the subjects. For classification purposes, the data were processed to determine maximum, minimum, range, and interval values. These interval values were then used to calculate the summation results for each classification category [24]. The classification results indicate that the brain activity of methamphetamine users can be mapped into five levels of addiction response, namely non-addicted, mildly addicted, moderately active, addicted, and highly addicted. Subsequently, the classified data were re-examined using the Naive Bayes method in MATLAB software to evaluate classification accuracy. The results of EEG feature extraction revealed significant differences across brain wave types among subjects [25]. The highest delta and theta wave activity was observed in S15, indicating deep relaxation, and drowsiness. Alpha waves were dominant in S1, reflecting a calm and relaxed state. In contrast, beta1, beta2, and gamma waves peaked in S8, suggesting heightened concentration and cognitive activity. Meanwhile, S5 recorded the lowest overall values, representing minimal brain activity. These variations highlight inter-subject differences in mental states and provide a crucial foundation for subsequent classification analysis.

Figure 3 presents a visualization of data distribution in the form of a scatter plot between several feature parameters and the output that represents the level of addiction response. The scatter plot of EEG band-power features (X-axis) against addiction scores (Y-axis) revealed a positive trend, with participants exhibiting higher EEG values generally showing higher addiction scores. The “Inactive” group, represented by blue dots, showed a concentration of lower values for both variables. The “Less Active” and “Active” groups, marked with purple and orange dots respectively, displayed more dispersed values within the mid-range. Finally, the “Tend to be Active” and “Very Active” groups, indicated by green and red dots.



(a)



(b)

Figure 2. EEG signal recording; (a) before filtering and (b) after BPF filtering

Table 1. Feature extraction

	Delta	Theta	Alpha	Beta1	Beta2	Gamma	Output
S1	12.47	8.22	10.09	1.2	0.98	0.49	33.45
S2	6,535	4.255	3,506	2.102	2,057	1.4	19,85
S3	9.84	4.71	4.71	3.03	4.55	2.35	29.19
S4	5.375	3.272	2,528	1,501	1.4	0.902	14,97
S5	2,734	2.106	1.984	0.881	0.875	0.621	9.201
S6	12.58	6.41	5.12	2.66	1.31	1.2	29.28
S7	3.358	2,759	2,519	1.178	1.245	0.797	11,85
S8	11.69	5.69	5.98	4.23	9.08	3.81	40.48
S9	0.98	3.91	6.84	13.67	19.53	29.3	74.23
S10	12.83	3.45	2.47	1.5	1.53	1.05	22.83
S11	10.73	5	3.55	1.54	1.66	0.9	23.38
S12	15.06	4.57	3.47	2.49	2.77	1.63	29.99
S13	12.83	3.45	2.47	1.5	1.53	1.05	22.83
S14	10.73	5	3.55	1.54	1.66	0.9	23.38
S15	19.7	12.52	3.81	1.13	0.73	0.38	38.27
S16	19.55	7.32	4.78	2.03	1.68	0.69	36.05
S17	3.33	2.19	2.17	1.09	1.05	0.49	10.32
S18	15.82	7.5	3.2	1.52	1.45	0.5	29.99
S19	8.27	4.78	2.97	0.84	0.98	0.64	18.48
S20	14.61	8.93	4.45	1.04	1.11	0.93	31.07
S21	10.28	8.63	6.74	2.19	2.76	1.35	31.95

In Figure 3(a), the non-addicted class is shown at low values with low output, while the less addicted and potentially addicted classes begin to spread at medium values. The addicted and highly active classes tend to appear at higher delta values, although there is still overlap between the classes. In Figure 3(b), the data distribution is more spread out. The non-addicted class remains dominant at low values, while classes with higher levels of addiction appear at higher values, but with significant overlap. In Figure 3(c), the distribution pattern is similar to beta1 but with a wider spread. Higher alpha values tend to decrease with increasing output, especially in the addicted and highly active classes. In Figure 3(d), the clearest class split is visible. The low-addicted class is at low to medium values, while the higher-addicted class is at higher theta values, indicating good discriminatory ability. In Figure 3(e), most of the data are displayed at low values, especially for the non-addicted and less addicted classes. Higher gamma values tend to be associated with the highly addicted class, but with a smaller amount of data, thus indicating a smooth distribution.

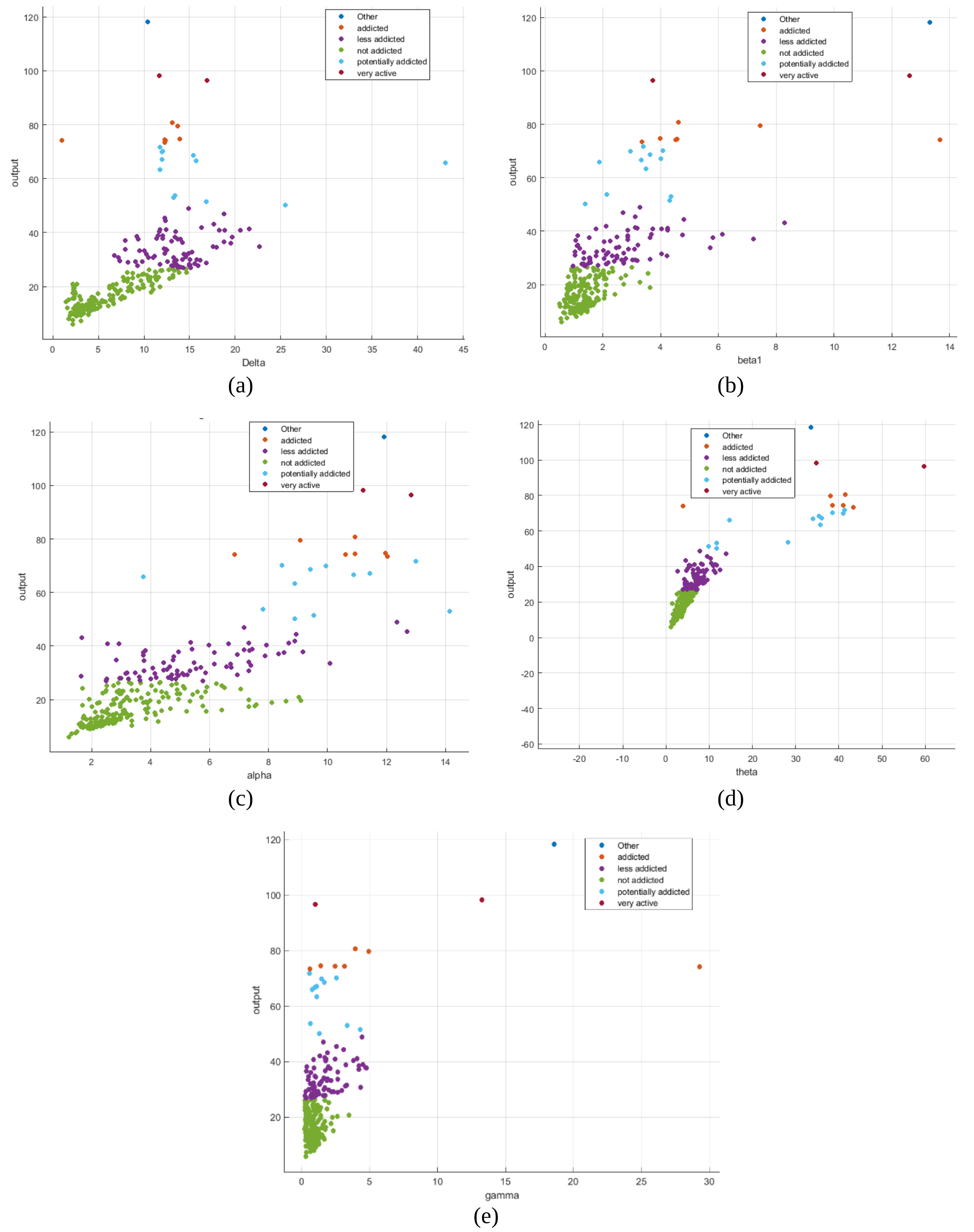


Figure 3. Scatter plot; (a) delta wave, (b) beta wave, (c) alpha wave, (d) theta wave, and (e) gamma wave

The confusion matrix in Figure 4 illustrates the distribution of individual classifications across activity categories. The majority of subjects were classified as "Inactive", while the "Active" category represented only a small portion. Categories such as "Less Active", "Tends to be Active", and "Very Active" contained very few samples, indicating an imbalanced data distribution across classes. Figure 4(a) displays the confusion matrix as a percentage. High diagonal values, such as for the non-addicted and less addicted classes, indicate that the model has a good level of accuracy in classifying both classes. However, for the potentially addicted and addicted classes, there are still quite significant classification errors, as indicated by off-diagonal values. Furthermore, the very active and other classes have high accuracy, but their data is relatively small and therefore less representative. As shown in Figure 4(b), the positive predictive value (PPV) was relatively high across most categories, suggesting that the classifier achieved good precision. However, the false discovery rate (FDR) was higher in minority categories, particularly "Less Active" and "Tends to be Active," reflecting reduced stability of predictions in these groups. Figure 4(c) presents the true positive rate (TPR) and false negative rate (FNR) for each class. The "Inactive" category achieved a very high TPR, while the "Active" category showed moderate performance. In contrast, minority classes, such as "Tends to be Active" and "Very Active," exhibited low TPR and high FNR, indicating that the model struggled to classify subjects in underrepresented groups accurately.

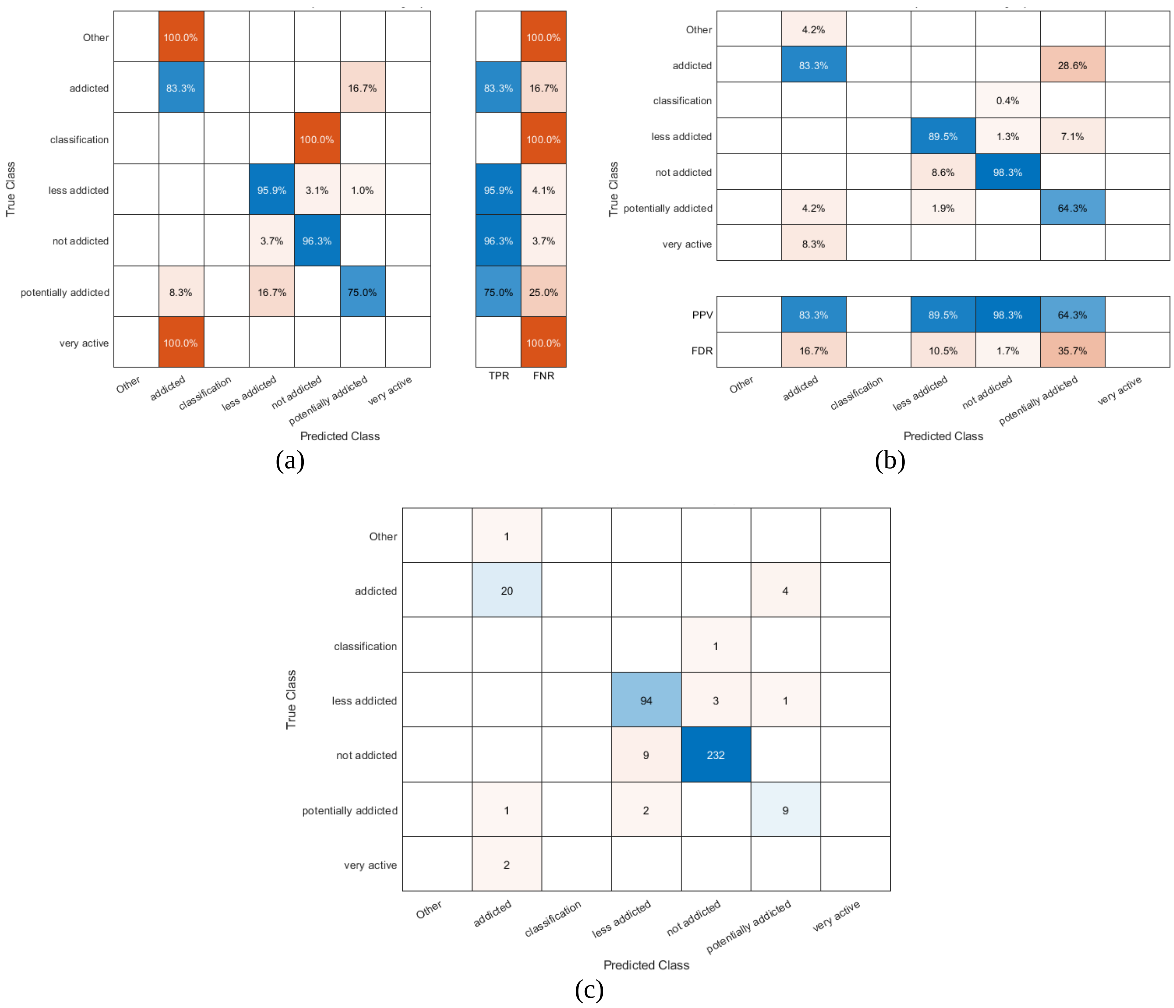


Figure 4. Confusion matrix; (a) TPR and FNR, (b) PPV and FDR, and (c) number of observations

The classification evaluation results indicate that the Naive Bayes method achieved an accuracy of 97.9% with a training time of 5.146 seconds. This method produced a precision of 98.2%, a recall of 97.9%, and an F1-score of 97.8%, demonstrating a high capability to classify the data accurately and consistently. Overall, these results indicate that Naive Bayes provides the best performance in terms of accuracy and training efficiency, while also emphasizing the important contribution of preprocessing and feature selection in enhancing classification accuracy. The t-test results indicated a significant difference with t=14.40, df=377, and p<0.0001. The mean output was 3.10 with a 95% confidence interval ranging from 2.68 to 3.52. The extremely small p-value confirms that this result did not occur by chance, indicating that the observed difference is statistically significant. These findings demonstrate that the tested variable has a real effect on the measured output.

Figure 5 shows the receiver operating characteristic (ROC) curve used as additional validation to evaluate the model's discriminatory ability in distinguishing addiction response levels. An area under the curve (AUC) value approaching 1 indicates that the algorithm can effectively differentiate between classes, reinforcing the reliability of the classification results [26]. The ROC analysis revealed that the Naive Bayes model effectively distinguished addiction levels, achieving an AUC of 0.95, which indicates excellent classification performance. The ROC curve's proximity to the top-left corner reflects high sensitivity and specificity across all thresholds. These findings are consistent with the high accuracy, precision, recall, and F1-score values, confirming the model's ability to correctly classify the majority of samples.

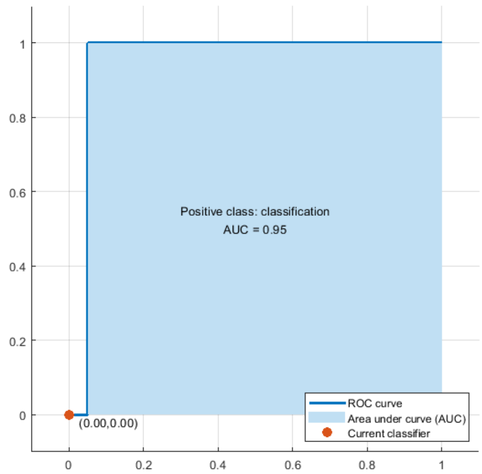


Figure 5. ROC validation

4. CONCLUSION

This study demonstrates that the Naive Bayes method can classify methamphetamine addiction levels based on EEG band-power features with excellent performance. The model achieved an accuracy of 97.9%, precision of 98.2%, recall of 97.9%, and an F1-score of 97.8%, highlighting its ability to consistently and accurately distinguish patterns of brain activity across different addiction levels. These findings have important implications for early detection of addiction, supporting individualized rehabilitation programs as well as forensic applications in assessing the risk of substance abuse. Future research may expand the model with larger sample sizes, incorporate additional EEG features, or explore alternative machine learning algorithms to further improve accuracy, address data imbalance, and strengthen predictions for underrepresented categories.

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CONFLICT OF INTEREST STATEMENT

Authors declare that they have no conflict of interest.

AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

DATA AVAILABILITY

Access to the data supporting the conclusions of this study may be granted by the corresponding author upon reasonable request.

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