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P300 EEG SIGNAL CLASSIFICATION USING RNN FOR COGNITIVE RESPONSE DETECTION

Nguyen Le Hoa[1)], Arjon Turnip[2)*], Dang Minh Quan[1)]

[1)]Faculty of Advanced Science and Technology, The University of Danang – University of Science and Technology, Vietnam
[2)] Department of Electrical Engineering , University of Padjadjaran, Indonesia

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ABSTRACT– P300-based EEG signals are a promising method for detecting brain responses to target and non-target stimuli. This study implements the Recurrent Neural Network (RNN) method to analyze and classify EEG signals recorded using a 19-channel EEG device based on the international 10–20 system standard. The preprocessing stage includes filtering to remove environmental noise and biological artifacts, followed by Independent Component Analysis (ICA) to ensure signal quality relevant for analysis. The results indicate that target stimuli produce higher P300 amplitudes and shorter latencies compared to non-target stimuli, with the Pz channel serving as the primary detection point. The RNN model achieved an average accuracy of 87.5%, precision of 88%, recall of 87.4%, and an F1-score of 87.7%. These findings confirm the reliability of RNN in capturing the temporal patterns of EEG signals and highlight its potential applications in neurotechnology, such as early detection of cognitive disorders and the development of neurofeedback systems.

KEY WORDS : Narcotics, EEG, P300, RNN, Classification, Methamphetamine

1. INTRODUCTION

Narcotics, psychotropics, and illicit drugs, or commonly referred to as drugs, in the health sector provide considerable benefits for human healing and safety [1][2]. However, drug abuse has become a serious problem in society, including in Indonesia. According to data from the National Police, since the beginning of 2024, there have been 33,924 cases of crime and drug trafficking, with an increase of 1.51 percent from August to September [3]. Drugs have significant negative impacts, including impaired cognitive, emotional, and behavioral function [4].

According to Fidrayani & Utami (2019), drugs have a significant impact on the work of the body, especially the brain. Research shows that drug addiction is linked to various cognitive deficits, such as emotion regulation, motivation, working memory, and decision-making [5]. By understanding the patterns of brain activity induced by drug use, it is hoped that interventions and rehabilitation programs can be designed more effectively to reduce the prevalence of drug abuse, especially among the younger generation [6].

Electroencephalography (EEG) is one of the most effective tools in understanding the impact of drugs on the brain. EEG records the brain's electrical activity that reflects changes in a person's emotions, cognition, and behavior. With relatively small amplitudes, ranging from 200 nanovolts to 2 microvolts, EEG signals can be analyzed to understand the frequency and amplitude characteristics of brain waves [7]. Analysis of brain wave frequencies, such as alpha (α), beta (β), theta (θ), and delta (δ), allows for a deeper understanding of memory responses to various stimuli, including the effects of drug use [8].

The main challenges in EEG signal analysis are the complexity of the data, noise, and individual differences between subjects. Traditional approaches, such as fast Fourier transform (FFT), have limitations in capturing nonlinear relationships in EEG data [9]. Alternatively, machine learning algorithms, including artificial neural networks and support vector machines (SVMs), have been used, but still face obstacles in identifying more complex nonlinear patterns [10].

Recurrent Neural Networks (RNNs) offer more advanced solutions for handling sequential data such as EEG signals. RNNs have the ability to store information from previous inputs through an internal state (memory), making them well-suited for data analysis involving context and temporal sequence [11][12]. In the context of this study, RNN was used to classify the effect of methamphetamine use based on the P300 pattern on EEG signals, which is expected to provide higher accuracy than traditional methods.

RNN technology not only provides new insights into the neurocognitive impact of methamphetamine use, but can also be used to support the rehabilitation process. With the ability to recognize complex patterns in EEG signals, RNN is expected to improve the effectiveness of the diagnosis and assessment of drug dependence levels. In addition, this technology can also help in evaluating the success of therapy during the rehabilitation process.

In recent developments, EEG is becoming more accessible, allowing research related to brain activity to be broader and more in-depth. The use of EEG in mapping the impact of drug addiction, especially on methamphetamine users, provides an opportunity to evaluate brain activity during withdrawal conditions. Research like this is important for understanding spectral changes in power at specific frequencies that reflect the neurocognitive activity that is affected [13].

RNN shows significant advantages in analyzing complex EEG signal patterns, especially in capturing temporal relationships that conventional algorithms cannot handle. Previous research has shown that RNN can be used to more accurately detect anomalies in the P300 pattern, which is an important indicator in the analysis of attention- and memory-related brain waves. This contributes to the development of diagnostic technologies that are more responsive to clinical needs in Indonesia [14].

The application of RNN in EEG analysis offers an opportunity to develop more accurate and non-invasive diagnostic methods. Utilizing local data, this study aims to explore the relevance and effectiveness of RNN in analyzing the impact of methamphetamine use in Indonesia. It is hoped that the results of this research can contribute to the development of better health technology and rehabilitation strategies in the future.

2. METHODOLOGY

This study was conducted using electroencephalography (EEG) to record the electrical activity of the brain of 40 inmates who used methamphetamine in the West Java Prison, Bandung City. EEG is an electrophysiological monitoring method that measures brain nerve activity. EEG signals depict brain conditions related to the human mental state, usually represented in low-voltage graphs over time [14]. The research site was chosen because it provides direct access to populations relevant to the research objectives as well as a controlled environment to ensure research ethical standards.

The process of recording EEG data begins with the placement of electrodes on the subject's head at a specific point, such as Fp1, Fp2, F3, Cz, O1, and so on, to effectively record the pattern of brain waves. EEG data was recorded in two conditions, namely the rest condition and after the subject was given visual stimulation in the form of a figure related to the use of methamphetamine. Stimuli were presented randomly to reduce bias, and experiments were repeated to improve the accuracy of the results.

After recording, EEG data is processed through a preprocessing step using WinEEG software. This step involves filtering high frequencies (50 Hz) and low frequencies (0.53 Hz) to eliminate unwanted noise. The filtered data is then converted into standard EDF format for further analysis.

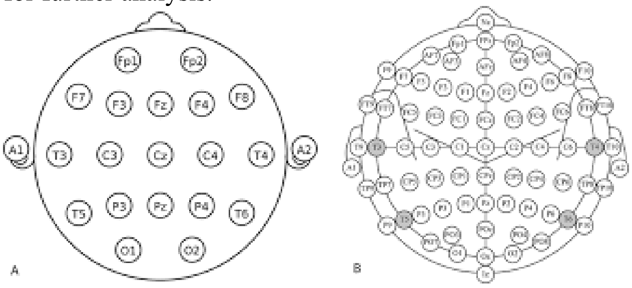


Figure 1. Electrode position of the EEG system 10/20

In this study, each subject was given stimulation in the form of a series of figures consisting of two categories: figures related to methamphetamine and figures not related to methamphetamine. The series of stimulation was carried out in 25 sessions, where each session consisted of 5 figures. Each Figure is displayed for 300 milliseconds (ms), with a 100 ms black screen pause between Figures. Thus, the total time required for data collection from each subject is about 50 seconds (50,000 ms). This procedure is designed to trigger the P300 response, which is an electrical potential that arises in the brain and can be recorded using an electroencephalography (EEG) device.

P300 is a component of a potential event-related (ERP) that usually appears about 300 ms after the cognitively relevant stimulus is administered. This component is often used to evaluate the process of attention and pattern recognition in the subject. In the context of this study, the difference in P300 responses is expected to reveal how subjects respond to figures related to methamphetamine compared to unrelated figures.

Data labeling was carried out by referring to the average value of the peak amplitude and latency of the ERP during the decision-making process (P300), according to the criteria listed in Table 1. The data was then grouped into four categories: active user/potential withdrawal, mild drug dependence, normal, and severe withdrawal. This classification is based on the amplitude and latency values measured during the research process.

Once the data has been labeled, the next stage is feature extraction to identify unique patterns or characteristics of EEG signals. This analysis aims to find a relationship between brain signaling patterns and drug dependence levels. In addition, the extraction capabilities of these features can be used in advanced research, such as detecting abnormal patterns or identifying specific types of drug use based on the EEG signal patterns detected. After the labeling stage, stages will be carried out to help the model using the Convulotional Neural Network (RNN),

EEG data analysis was carried out using a deep learning approach based on repetitive neural networks (RNNs). This approach is particularly effective for detecting patterns in EEG signals due to RNN's ability to process sequential data [15, 16]. The RNN model was used to analyze the pattern of brain activity from EEG signals, which included amplitude characteristics, dominant frequencies, and components of P300 that are important in methamphetamine-addiction-related studies.

With RNN's ability to capture sequential patterns, the algorithm is able to analyze complex relationships that are difficult to identify by traditional methods. This approach allows for the identification of brain patterns related to methamphetamine dependence levels with high accuracy. The results of this analysis not only provide scientific insights, but also become supporting data in the early detection of neurological disorders in methamphetamine users.

$$\mathbf{h}_t = \sigma_h(\mathbf{W}_{xh}\mathbf{x}_t + \mathbf{W}_{hh}\mathbf{h}_{t-1} + \mathbf{b}_h). \qquad (1)$$

where $\mathbf{W}_{xh}$ is the weight matrix between the input layer and the hidden layer, $\mathbf{W}_{hh}$ is the weight matrix for the recursive connection, $\mathbf{b}_h$ is the refractive vector, and σ_h is the activation function, which is usually a hyperbolic tangent (tanh) function or rectified linear unit (ReLU) [41,42]. The output at each time step, tt, is given by the following equation:

$$\mathbf{y}_t = \sigma_y(\mathbf{W}_{hy}\mathbf{h}_t + \mathbf{b}_y). \qquad (2)$$

where $\mathbf{W}_{hy}$ is the weight matrix between the hidden layer and the output layer, $\mathbf{b}_y$ is the bias vector, and σ_y is the activation function for the output layer.

Using various metrics such as accuracy, precision, recall, and F1 score. This metric is used to evaluate how accurately a model can classify data, especially when differentiating positive and negative classes. In addition, the confusion matrix is also used as a visual aid to show the distribution of true and false predictions. This matrix helps you determine the types of misclassifications that occur. Evaluation based on these indicators provides a comprehensive Figurean of the strengths and weaknesses of the developed model. A block diagram of the entire research process is shown in Figure 2.

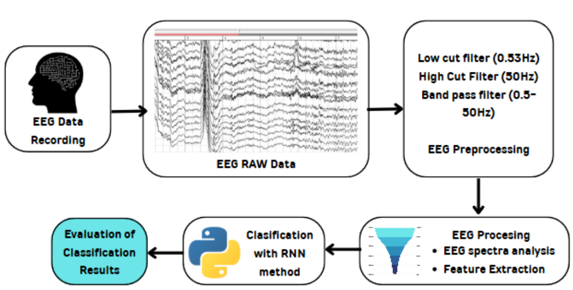
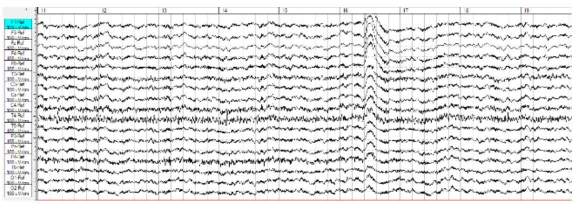


Figure 2. Research scenario

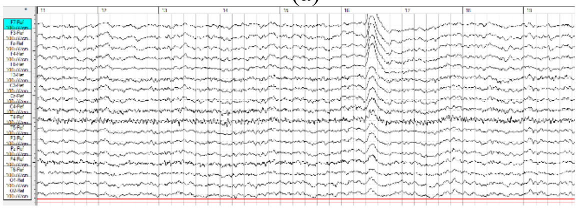
3. RESULTS AND DISCUSSION

This study involved 40 inmates who used methamphetamine from the Bandung City Prison as subjects. EEG data was recorded using a Mitsar 202-24 device and a cap electrode with 19 channels, installed according to the international standard of 10-20 systems. The electrodes used include Fp1, Fp2, F7, F3, Fz, F4, F8, T3, T4, T5, T6, C3, Cz, C4, P3, Pz, P4, O1, and O2, covering the frontal, parietal, temporal, and occipital areas of the brain, to record relevant patterns of brain activity. Subjects were given stimulus in the form of a series of figures consisting of two categories: methamphetamine-related figures and other figures. Stimulation was carried out in 25 sessions, each consisting of 5 Figures, with a viewing duration of each Figure of 300 ms and a pause between figures in the form of a black screen of 100 ms. This process resulted in a total data collection time of about 50 seconds (50,000 ms) per subject. This approach aims to trigger the P300 response, which is the brain's electrical potential measured through electroencephalography (EEG).

In this study, EEG signals were classified using the P300 method to identify the brain's response to the target stimulus. One of the main obstacles in EEG signal analysis is noise interference caused by movement artifacts, muscle activity, or environmental factors. Therefore, the initial stage of signal processing is carried out to reduce the effects of noise, including filtering techniques to eliminate irrelevant frequencies as well as data normalization to detect latency patterns. For example, Figure 3 shows a comparison of EEG signals before and after filtering using a low-cut filter at a frequency of 0.53 Hz, a high-cut filter at a frequency of 30 Hz, and a filter bandpass for a specific frequency range.



(a)



(b)

Figure 3. Comparison of filtration result, (a) Before filtering, (b) After filtering

The EEG signal before filtering displays noise with disturbing amplitudes at various frequencies, especially below and above 0.5 Hz. After the 30 Hz filtering process, the noise is successfully suppressed, resulting in a cleaner EEG signal that corresponds to the physiological frequency range of the brain, thus facilitating the analysis of relevant signals in EEG studies. Graph in Fig.5. shows a comparison of P300's response to brain signals under two conditions namely, target (labeled with a blue line) and non-target (labeled with a red line). The X-axis in ms represents time ranging from -200 to 800 ms. At the point 0 ms is given a dotted black vertical line indicating the onset of the stimulus, i.e. when the stimulus is given to the subject. The Y-axis or amplitude in microvolts is measured by the brain's response to stimuli. The green line on the graph shows the time window of p300 (a time range of about 300 to 600 ms). P300 which is an Event Related Potential (ERP) component appears about 300 ms after the subject recognizes the relevant stimulus. The blue curve (target) represents the brain's response to the target stimulus, and the red curve (non-target) represents the response to the non-target stimulus. Both star points mark the peak of amplitude in both target and non-target responses. For example, in blue stars it has a value of 16.87 microvolts, and in red stars 3.40 microvolts. The significant difference between the two peaks illustrates the brain's differential response to target and non-target stimuli, as shown in Figure 4.

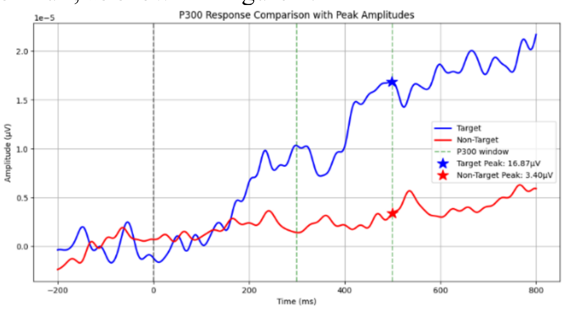


Figure 4. Wave response in S1

The initial data processing step includes Bandpass Filter Bandpass filters in the range of 0.1–30 Hz are applied to eliminate irrelevant noise, such as environmental disturbances and tool noise. The frequency includes a physiological range relevant to brain activity, including the detection of P300 patterns. In Figure 1(a), the raw EEG signal shows significant interference, while Figure 1(b) shows a cleaner signal after filtering. This cleansing ensures that the recorded brain activity is relevant to further analysis. Electrical Network Noise Removal Electrical network noise (50 Hz) originating from interference from electronic devices is successfully removed using a notch filter. This is important to prevent signal distortion that can affect EEG pattern detection, particularly the P300, which is highly sensitive to external interference.ICA's Independent Component Analysis (ICA) is used to detect and mitigate artifacts such as eye movements and blinking. Based on the processing results, these artifacts were successfully minimized, reflecting that the data obtained was clean and optimal for P300 pattern analysis.

After the cleansing process, the EEG signal is processed into 125 epochs per subject, consisting of 25 targets and 100 non-targets. The analysis time range is focused on the 250–500 ms window after the stimulus, where P300 generally appears.

Table 1 summarizes the comparison of the average amplitude and latency of the P300 in the main canals: frontal (Fz), central (Cz), and parietal (Pz). These channels have different roles in cognitive processing: Frontal (Fz): Responsible for attention and executive function. Central (Cz): Plays a role in motor and sensory integration.mParietal (Pz): Focuses on target detection and cognitive integration.

The P300 pattern showed a much higher amplitude at target conditions than non-targets, reflecting greater cognitive activity on the recognition of relevant stimuli. The Pz canal shows the highest amplitude, which is consistent with the literature that the parietal area plays an important role in target detection. Shorter latency at the target condition indicates the efficiency of the brain's processes in recognizing important stimuli.

Table 1. Table of Channels, Amplitude and Latency

Canal	**Target Amplitude (µV)**	**Non-Target Amplitudo (µV)**	**Latensi Target (ms)**	**Latensi Non-Target (ms)**
Fz	8.23 ± 1.15	2.67 ± 0.85	320 ± 20	340 ± 25
Cz	7.89 ± 1.08	2.54 ± 0.92	315 ± 22	345 ± 30
Pcs	9.12 ± 1.20	3.01 ± 0.88	310 ± 18	335 ± 27

This shows the difference in amplitude and latency between the target and non-target. The Pz canal has the highest amplitude, which confirms the dominance of the parietal area in the recognition of the target stimulus. The shorter latency of P300 in target conditions suggests that this stimulus triggers a faster brain response than non-targets.

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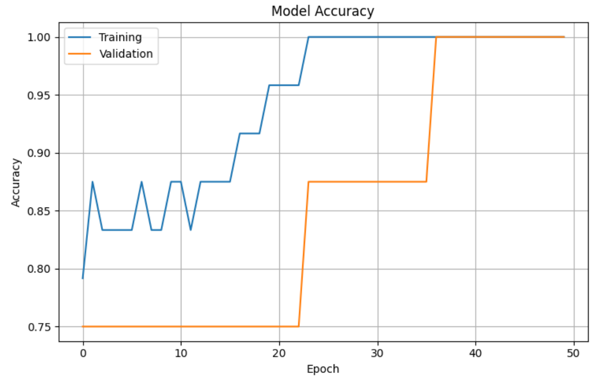
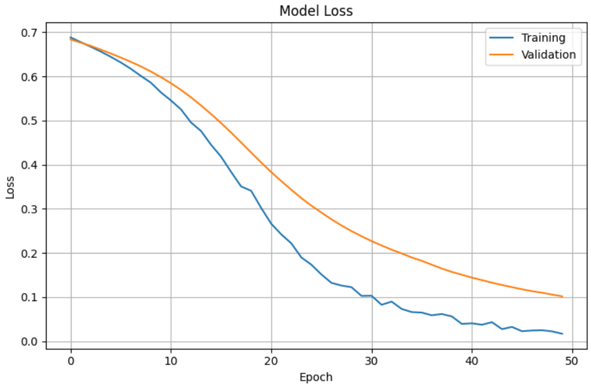


(a)



(b)

Figure 5. (a) accuracy model (b) loss model

Furthermore, the Evaluation of Model Accuracy with the accuracy graphs (a) and (b) of the model showed that the training accuracy increased gradually from about 0.75 in the first epoch to close to 1.0 in the 50th epoch. This indicates that the model learns well from the training data. Meanwhile, the validation accuracy remained constant at around 0.75 until the 30th epoch, before increasing sharply starting from the 40th epoch and reaching a value equal to the training accuracy, which was about 1.0 at the end of the training. A sudden increase in validation accuracy like this might indicate the model is taking longer to learn from the validation data, but it can also be a sign of overfitting, where the model is over-memorizing the training data.

On the loss model chart, training losses decline consistently from about 0.7 in the first epoch to close to 0.0 in the 50th epoch. This shows that the model continues to optimize the parameters on the training data. Validation losses also decreased from 0.7 to around 0.2 at the end of training, but the difference with training losses began to be noticeable after the 10th epoch. This difference reinforces an indication of overfitting, where the model performs very well on training data but is less able to handle new data or validation data.

Quantitatively, the training accuracy increased from 0.75 to 1.0, while the validation accuracy increased from 0.75 to 1.0 after stagnation until the 30th epoch. For losses, training losses decreased from 0.7 to 0.0, while validation losses decreased from 0.7 to 0.2. Based on these results, measures such as the use of regularization (dropout or L2 regularization), addition of training data, or cross-validation can be undertaken to reduce overfitting and improve the generalization capabilities of the model.

The evaluation of the performance of the RNN model in analyzing EEG signals was carried out based on accuracy, precision, recall, and F1-score metrics. Table 2. summarizes the results of the evaluation for the target and non-target classifications.

Metric	**Target (%)**	**Non-Target (%)**	**Installment-Installment (%)**
Accuracy	89.5	85.3	87.5
Precision	91.2	84.7	88.0
Recall	88.7	86.0	87.4
F1-Score	89.9	85.4	87.7

The RNN method is used to utilize temporal patterns in EEG signals, specifically to detect differences between target and non-target conditions. The RNN architecture consists of several layers designed to capture temporal relationships in the dataIn this study: Temporal Capabilities: RNN can study patterns of P300 amplitude and latency changes over time, which cannot be captured by static methods. Data Generalization: The RNN model exhibits high generalization capabilities, with an average accuracy of 87.5%, proving its reliability in classifying EEG signals into target and non-target categories. Cognitive Process Efficiency: By using RNNs, complex P300 patterns can be translated into relevant features for classification, demonstrating great potential in neurotechnology-based applications.

These results demonstrate the superiority of RNN in temporally capturing the dynamics of P300 patterns, opening up further opportunities for applications such as cognitive impairment detection or neurofeedback. Based on the results summarized in Table 2, the RNN model shows strong performance in the classification of EEG signals. The average accuracy of 87.5% indicates the model's ability to distinguish between target and non-target patterns well. The high precision and recall, particularly on targets, reflect the model's ability to detect relevant stimuli with low error rates.

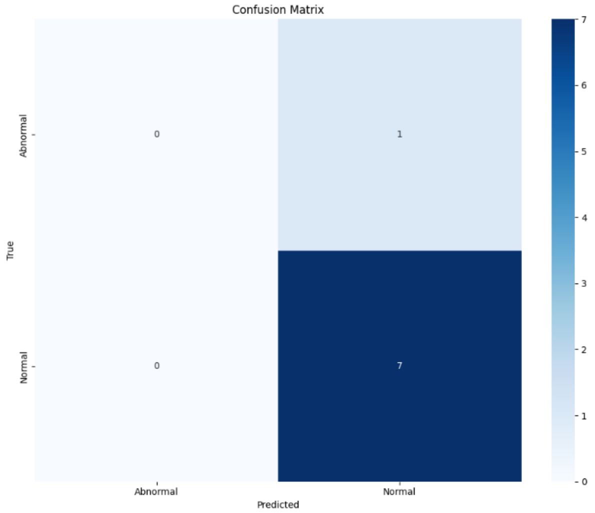


Figure 6. Confusion matrix

4. CONCLUSION

This study shows that the RNN (Recurrent Neural Network) method is effective in analyzing and classifying P300-based EEG signals to distinguish the brain's response to target and non-target stimuli. The process of recording signals using an EEG device with 19 channels at the international system standard of 10-20 produces representative data of the activity of the frontal, parietal, temporal, and occipital areas. Preprocessing processes, such as filtering to remove environmental noise and biological artifacts, as well as ICA techniques, ensure clean and relevant signals for analysis. Analysis showed a higher amplitude of P300 and shorter latency on the target stimulus compared to non-targets, with the Pz channel as the highest detection center. The RNN model showed an average accuracy of 87.5%, with an accuracy of 88%, recall of 87.4%, and an F1-score of 87.7%, reflecting its reliability in capturing the temporal pattern of EEG signals. These results not only confirm the effectiveness of the RNN method in detecting P300 patterns but also open up opportunities for the development of neurotechnological applications, including the detection of cognitive impairment or neurofeedback systems.

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