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Unlocking Early Detection and Intervention Potential: Analyzing Visual Evoked Potentials in Adolescents/ Teenagers with Narcotics Abuse Tendencies from the TelUnisba Neuropsychology Electroencephalograph Dataset

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ABSTRACT Narcotics abuse has severe negative impacts on individuals, families, and society, including physical harm and mental health disorders. Addressing narcotics issues among teenagers requires collaborative efforts from educational institutions, families, and psychologists. This study aims to propose a method for early detection of narcotic abuse in adolescents. The key contributions of this study are the introduction of the TelUnisba Neuropsychology Electroencephalograph Dataset called TUNDA, which provides rich 2D EEG signal data for drug abuse research in Indonesia, the use of MobileNetV2 architecture for classifying EEG signals, achieving high accuracy, the demonstration of the effectiveness of 2D EEG signal representation in capturing detailed neural responses, and the potential application of these findings in developing early intervention and prevention strategies for narcotic abuse among adolescents. The TUNDA dataset is an open electroencephalograph dataset with data on the emotional and habitual aspects of drug abuse in Indonesia, classified into "normal" and "risk" by psychologists. The processed electroencephalograph signal is the Visual Evoked Potential within 1000 milliseconds following the visual stimulus onset. The data is classified as "slow" and "fast" based on respondents' responses using MobileNetV2 architecture. Results showed MobileNetV2 achieved the highest accuracy for both normal and risk categories, with accuracies of 0.86 and 0.85 respectively. In conclusion, while the study demonstrates high accuracy in classifying narcotic abuse tendencies using MobileNetV2 and the TUNDA dataset, the small sample size and high computational demands limit its generalizability and broader implementation. Future research with larger, more diverse samples and optimized computational methods is needed to validate and expand these findings.

INDEX TERMS Electroencephalograph, Go/No-Go Association Task, MobilenetV2, Neuropsychology.

I. INTRODUCTION

Narcotics and psychotropics have valuable medical applications but can also lead to severe dependence and misuse owing to their versatility and processing possibilities in the context of advancing science and technology. The World Drug Report 2022 offers a comprehensive analysis of the global illegal drug market and explores the connections between drugs and the environment within the broader context of sustainable development goals, climate change, and environmental sustainability. In 2020, an estimated 284 million individuals aged 15-64 worldwide, primarily males, had used narcotics in the past year, representing approximately 5.6 percent of that age group, marking a 26 percent increase from 2010 when there were 226 million drug users, with a 5 percent prevalence rate. This increase can be partially attributed to global population growth [1].

According to a survey conducted by the National Narcotics Agency, known in Indonesia as Badan Narkotika Nasional (BNN), in collaboration with the Center for Data and Information Study in 2021, there was a significant increase in the prevalence of drug use within a year between 2019 and 2021, particularly among the age group of 15-29 years old. The data indicated that in the 15-29 age group, the prevalence rate increased by 128.75%. This increase in drug use among the 15-29 age group highlights the need for attention and efforts to educate people about drug abuse [2].

In response to the increasing use of drugs, psychologists play a vital role in addressing this issue, particularly in teenagers. They employ a keen understanding of addiction terminology and the subtle nuances of narcotics in word choice when working with young people. Psychologists often use neurodata to observe and assess the impact of substance abuse on teenage brains. By analyzing neural patterns and cognitive responses, they gained insights into how drug use affects the developing brain, helping to tailor interventions and educational programs to mitigate the rising prevalence of drug abuse among youth.

Understanding the functions, behaviors, and cognitive processes of the human brain is an intriguing subject of study for healthcare experts, who aim to find solutions to address issues related to the human brain [3][4]. Numerous neuroscience-based studies have found that variability in neural processing within the human brain is limited, and this variability can lead to disruptions in brain performance [5]. How an individual responds to stimuli from their environment, whether intentional or unintentional, generates different signals in the brain and can be detected through the brain-computer interface (BCI) system, one of which is electroencephalography (EEG) [6].

EEG extracts brain signals with the aid of neuronal potentials, which can be further stored as voltage pulses [7]. EEG signals find extensive applications in biomedicine, encompassing the diagnosis and monitoring of conditions such as epilepsy and sleep disorders, cognitive studies, brain-computer interfaces, and mapping brain activity in neurological disorders. They serve as versatile tools for understanding brain function, aiding in diagnosis, treatment, and study across a wide spectrum of biomedical and neurological conditions. EEG can be processed using one dimension and two-dimension signal. The feature values from all EEG channels were arranged in two different composite feature forms: a 1D form that places the channel features one after another in a sequence, capturing electrical activity at a single electrode over time, and a 2D image-like form that arranges the individual channel features in rows, providing a spatial map of electrical activity across multiple electrodes on the scalp along with the temporal dimension [8].

Most EEG signal recording data are typically presented in the form of one-dimensional data. Signal processing is essential for analyzing one-dimensional EEG signal data. Common signal processing techniques used for one-dimensional signal analysis include finding energy values, spectrograms, and utilizing the Hilbert-Huang transform (HHT) [9]. However, with the most available datasets, specialized techniques are required for analysis. There are alternative methods for EEG signal analysis; however, two-dimensional signal plotting methods are rarely used. This is because the existing datasets do not support such analyses. Two-dimensional EEG signal data represent energy images within the brain [10].

EEG signal processing has played a pivotal role in recent studies on emotion recognition and motor imagery classification. Studies have explored the transition from 1D to 2D EEG signal representations, which have resulted in improved accuracy. Yang et al. [11] achieved an 84.21% accuracy in emotion recognition using 1D EEG signals, whereas Wang et al. [12] achieved a high accuracy of 90.59% by employing a Convolutional Neural Networks (CNN) on 2D EEG signals using the SEED dataset. Similar trends were observed in motor imagery classification by Kanoga et al. [13] reaching an accuracy of 87.6% using 1D EEG signals. Tanvir et al. [14] achieved an impressive accuracy of 97.7% by converting time-series EEG signals into 2D images using the BCI Competition IV dataset. This shift towards 2D EEG representations underscores their potential to capture richer information and enhance the classification performance.

Furthermore, across various domains, including image classification and EEG signal analysis, the MobileNetV2 architecture has gained widespread popularity. Its advantages, such as the efficient handling of low-dimensional inputs, reduced computational complexity, and high accuracy while conserving memory resources, make it a versatile choice for deep learning tasks [15]. Kolonne et al., Hu et al. and Tobias et al. used MobileNetV2 to distinguish between pneumonia types and others from chest X-ray images, with an accuracy of more than 96% [16], [17], [18]. Arani et al. [19] using MobilenetV2 to correctly identify malignant or non-melanoma tumours, with an accuracy of over 94%. Shankey et al. used MobileNetV2 to classify breast cancer, resulting in a final accuracy of 92 % [20]. The adoption of MobileNetV2 reflects its ability to deliver rapid and accurate results during biomedical signal preprocessing.

Telkom University (TELU) and Universitas Islam Bandung (UNISBA) collaborated in a study focusing on the risks of drug abuse and addiction terminology in Indonesia. This innovative study provided a fresh perspective by analysing EEG signal data related to the emotions and psychological habits of drug users in Indonesia, particularly among participants aged 16 to 19 years. The study included 12 high school students, categorized into normal participant and risk participant. This study introduced a new EEG dataset, the TelUnisba Neuropsychology EEG Dataset (TUNDA), which can be publicly accessed. TUNDA serves as a valuable source of EEG signal data on the emotional and habitual aspects of drug abuse in Indonesia. TUNDA contains two-dimensional (2D) EEG signal plotting data and offers versatile options for EEG signal analysis. The 2D data processed is in the form of a topological plot of the EEG signal in the visual evoked potential (VEP) period with a duration of less than 1000 milliseconds after each visual stimulus is given. The inclusion of two-dimensional signal plotting opens various possibilities for analysis, such as medical image classification, object recognition in computer vision, emotion and expression identification, and data screening.

This study aims to develop a method for the early detection of narcotic abuse among adolescents through the analysis of 2D EEG signal data. The proposed method utilizes the TUNDA dataset, which offers comprehensive 2D EEG signal representations specifically collected for drug abuse research in Indonesia and employs the MobileNetV2 architecture to classify these signals. By focusing on identifying neural patterns that may indicate drug abuse, this approach aims to improve the detection and prevention of narcotic abuse among adolescents. The key contributions of this study are: (1) the introduction of the TUNDA dataset, providing rich 2D EEG signal data for drug abuse research in Indonesia, (2) the use of MobileNetV2 architecture to classify EEG signals, achieving high accuracy, (3) the demonstration of the effectiveness of 2D EEG signal representation in capturing detailed neural responses, and (4) the potential application of these findings in developing early intervention and prevention strategies for narcotic abuse among adolescents.

II. MATERIALS AND METHOD

Generally, the method used to observe emotions involves the use of interview results combined with video recordings. This method is commonly used but can still be manipulated by the participants. GNAT combined with the recording of 16 Channels EEG signal was chosen as the data-recording method. With GNAT, participants were required to provide responses as quickly as possible, and EEG signal recording was performed under these conditions. With this method, participants find it difficult to manipulate existing data. In the analysis process, EEG signals were converted into 2D form and analyzed using deep learning methods, specifically using MobileNetv2.

A. GO/NO GO ASSOCIATION TASK (GNAT)

The measurement instrument used was the GNAT (Go/No Go Association Task (GNAT), which was designed to assess implicit association variables. This computer-based measurement instrument utilized a program designed to generate stimuli in accordance with the study objectives. The GNAT is a cognitive task used in psychology and neuroscience to measure response inhibition. In this task, participants are required to respond to a specific stimulus (Go signal) by pressing a button, while refraining from responding when a different stimulus (NoGo signal) is presented. In the GNAT process, the instrument presents two types of stimuli: targets and distractors [21],[22]. In this study, the stimuli employed were word_1: *narkoba* (Indonesian Language: drugs used in negative terms); word_2: *napza* (Indonesian Language: drugs used in positive terms); word_3: *penyalahguna* (Indonesian Language: abuser used in positive terms); and word_4: *pecandu* (Indonesian Language: addict used in negative terms). The stimuli were grouped into target categories. The other stimuli used were words representing "positive" and "negative" as the evaluative categories.

Table 1. GNAT Design Used

Blocks	**Tasks**	**Trials**	**Stimuli (*words are in Bahasa Indonesia*)**
1	Practice	20	Target: *Narkoba*, Distractor: *NAPZA*
2	Practice	20	Target: *NAPZA*, Distractor: *Narkoba*
3	Practice	20	Target: *Pecandu*, Distractor: *Penyalahguna*
4	Practice	20	Target: *Penyalahguna*, Distractor: *Pecandu*
5	Practice	20	Target: *Positive*, Distractor: Negative words
6	Practice	20	Target: Negative, Distractor: Positive words
7	Trial Task 1	16	Target: *Narkoba* or Positive words, Distractor: *NAPZA* or Negative words
8	Main Task 1	60	
9	Trial Task 2	16	Target: *Narkoba* or Negative words, Distractor: *NAPZA* or Positive words
10	Main Task 2	60	
11	Trial Task 3	16	Target: *NAPZA* or Positive words, Distractor: *Narkoba* or Negative words
12	Main Task 3	60	
13	Trial Task 4	16	Target: *NAPZA* or Negative words, Distractor: *Narkoba* or Positive words
14	Main Task 4	60	
15	Trial Task 5	16	Target: *Pecandu* or Positive words, Distractor: *Penyalahguna* or Negative words
16	Main Task 5	60	
17	Trial Task 6	16	Target: *Pecandu* or Negative words, Distractor: *Penyalahguna* or Positive words
18	Main Task 6	60	
19	Trial Task 7	16	Target: *Penyalahguna* or Positive words, Distractor: *Pecandu* or Negative words
20	Main Task 7	60	
21	Trial Task 8	16	Target: *Penyalahguna* or Negative words, Distractor: *Pecandu* or Positive words
22	Main Task 8	60	

During the GNAT task, participants are required to respond with either "go" or "no go" based on the provided instructions and within a specified reaction time of 1000 ms [22]. In the execution of the Go/No-Go Association Task (GNAT),

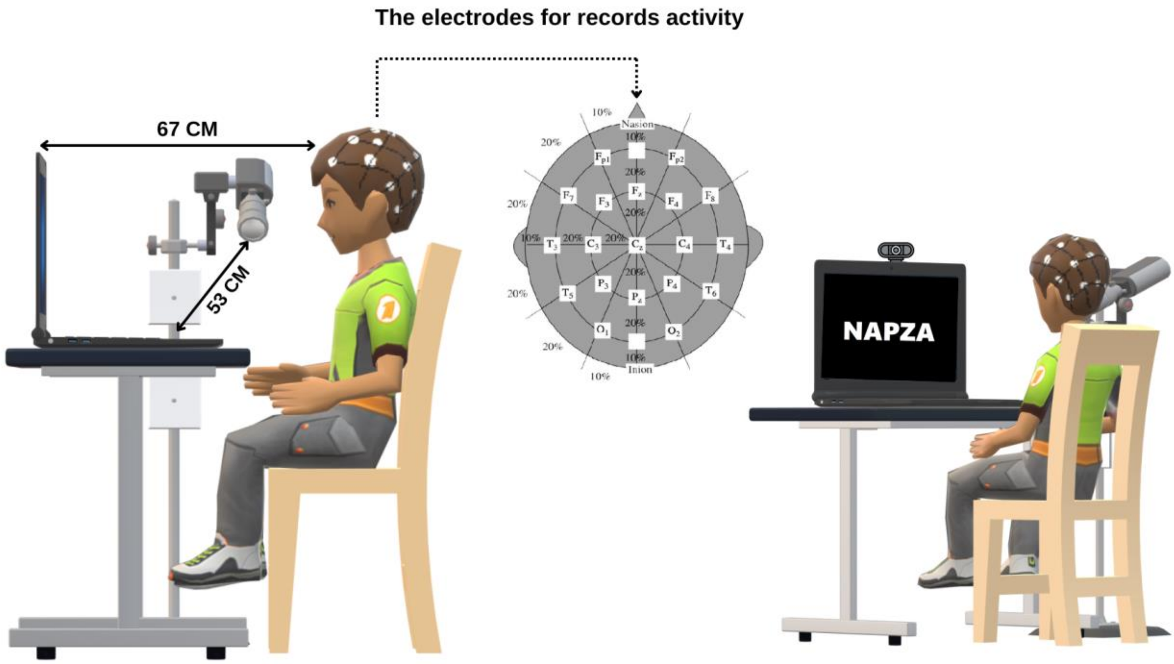


FIGURE 1. **Illustration of The EEG Signal Recording**

participants need to respond "Go" by pressing the spacebar when a target word appears and respond "No Go" by not pressing any key when a distractor word appears [23].Participants were tasked with completing 22 tasks in the GNAT, which were divided into two sections: the practice session and the main session. During the practice session, the participants were familiarized with the general GNAT process, beginning with the emergence of stimuli and instructions on responding to the appropriate stimuli. This section comprises of six tasks. Upon completion of the practice section, the session transitions to the main session, which includes eight main tasks, each initiated by one trial task [23]. During the test session, participants underwent 16 trials for the trial task and 60 trials for the main task, as outlined in TABLE 1.

During the GNAT process, Psychologists from the Psychology Department at UNISBA observed the behaviour and body movements of the participants. Subsequently, psychologists interviewed the participants. There were two participant criteria specified by psychologists: normal (represented by "N") and at-risk (represented by "R"). Psychologists determined participant criteria based on predetermined parameters. In GNAT, the strength of an association is evaluated by considering the distance of items, such as words, from the target category. Additionally, attributes (e.g., traits and objects) not directly related to the target words may serve as distractors that are not part of the target words. One condition involves the simultaneous identification of stimuli representing the target category and distractors [22], [23].

B. RECORDING SETUP

Data recording was performed at the Smart Data Sensing Laboratory of Telkom University, Bandung. The target participants for the primary dataset collection were 12 high school students aged 16–19 years. The participants were provided with a questionnaire related to their readiness and condition before taking the GNAT. The purpose of this questionnaire was to determine whether the participants had ever been exposed to drug-related matters. The results of the questionnaire will categorize the participants into two groups: those who have some involvement with drugs, categorized as "at-risk" participants, and those who are not involved with drugs, categorized as "normal".

The EEG recording device used was the Contect KT-88 1016, which has 16 channels and 100 Hz of sampling frequency. The EEG recording setup in this study was designed to make participants feel comfortable during the recording process. The experimental setup is illustrated in FIGURE 1. The monitor screen used as the test medium was positioned 67 cm from the participant. This distance was chosen because it represents the average comfortable working distance in front of a monitor screen, as suggested by the American Optometric Association, with a recommended distance for working in front of a monitor screen being 45-75 cm [24],[25].

A KT-88 device was placed behind the participants with camera was positioned facing the participant's face and hands to record the participant's activities during the test. A front camera was used to capture the participant's face and various body movements during the test. Additionally, there is a camera placed on the side of the table positioned 53 cm away and aimed at the keyboard to record the participant's activities and serve as a means of validation when the participant presses the keyboard keys.

FIGURE 2 shows the placement of each device necessary for EEG signal data recording. Each placement has specific distances, such as the distance between the respondent and the screen, which is 67 cm. This distance is chosen for the comfort of working in front of a monitor. The distance from the body to the keyboard is 47 cm, which is the average comfortable distance for respondents to reach the keyboard during the test. This distance can be adjusted according to the respondent's comfort. There are cameras directed at both the keyboard and the respondent's face. The camera's purpose is to record the respondent's condition while performing the GNAT test. The camera aimed at the respondent's face is placed above the monitor, making its distance the same as the monitor's, which is 67 cm. The camera directed at the keyboard is placed to the respondent's right side, 53 cm from the table.

FIGURE 3 shows the process of EEG signal recording. The room lighting is designed to be dimmer to help the respondent focus solely on the GNAT test. The room conditions during EEG signal recording are crucial. 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.

The recording results capture the respondent's performance during the GNAT, as shown in FIGURE 4. The recording includes footage of the respondent's face on the left side and the GNAT screen being worked on by the respondent on the right side of the video. Timestamps are included in the format of hh:mm,ms (e.g., 00:04:24,78) to help psychologists analyze the respondent's facial expressions and responses while pressing the spacebar during the GNAT test. In addition, the recording also captures EEG signals during the GNAT in one dimension, as shown in FIGURE 5.

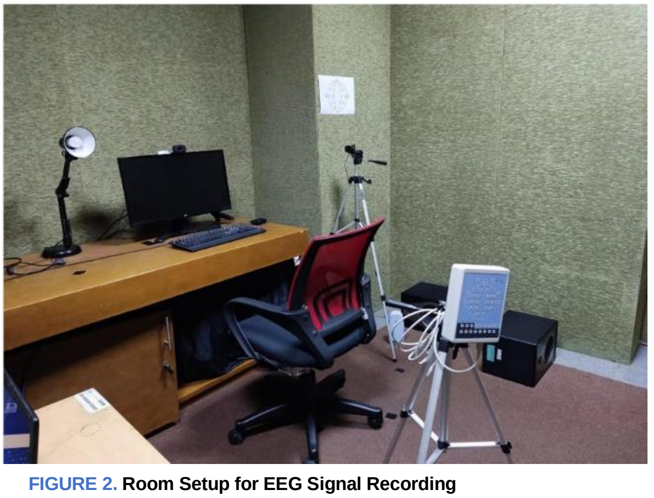


FIGURE 2. Room Setup for EEG Signal Recording

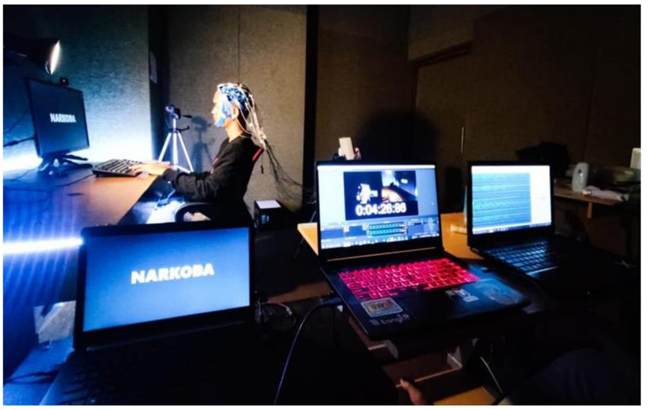


FIGURE 3. Process of EEG Signal Recording from Operator View

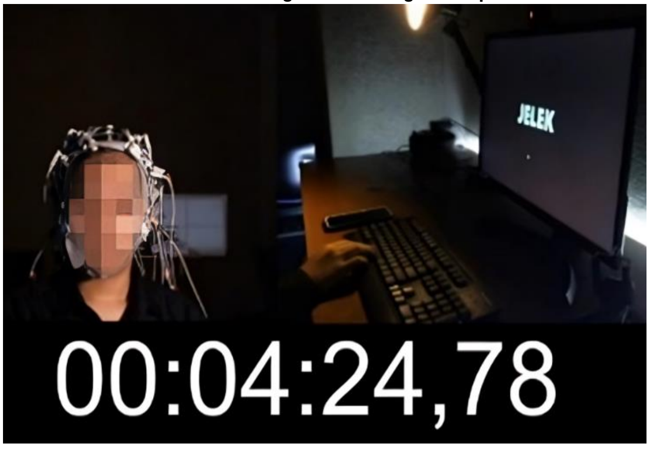


FIGURE 4. Video Recording Result with Timestamps

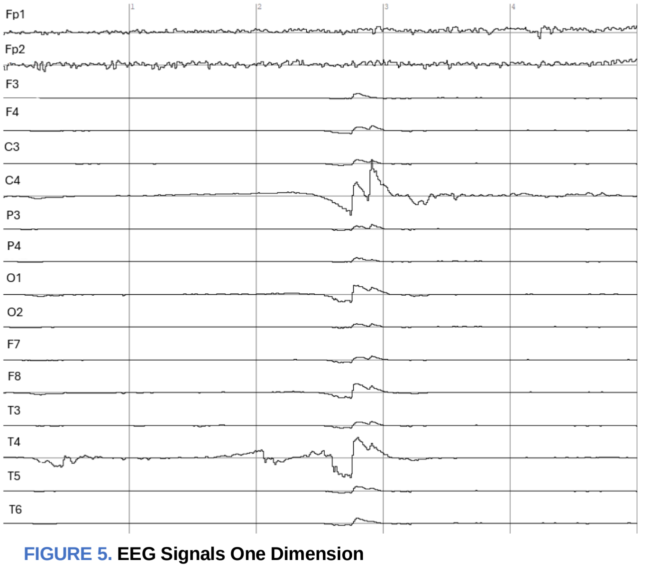


FIGURE 5. EEG Signals One Dimension

C. EEG DATASET

In Indonesia, there is still a lack of EEG signal recording data related to emotions and psychological habits. Typically, EEG signal datasets on platforms such as Physionet, GitHub, and DEAP primarily focus on diseases. Furthermore, in neuropsychology, acquiring localized data is essential to support ongoing research on issues discussed by direct sampling from the local environment. In this study, we introduced an open EEG dataset called the TelUnisba Neuropsychology EEG Dataset (TUNDA). TUNDA serves as a valuable source of EEG signal data on the emotional and habitual aspects of drug abuse in Indonesia. TUNDA contains two-dimensional EEG signal plotting data and offers versatile options for EEG signal analysis. This 2D data is the result of converting time series EEG signals into topology plots. The processed EEG signal has a duration of less than 1000 milliseconds which is called VEP when each stimulus is given.

The recorded data split into two categories "normal" and "risk" based on the classification from Psychologists. Participants in the "Normal" category were those who had never been involved with drugs. While the "At Risk" category is those who was involved with drugs themselves or have relatives who have had such involvement. Each category is then divided into "fast" and "slow" response based on the response in pressing the space bar. For a response below 0.5s it is considered fast while the other is slow.

There were seven participants in the normal group, with 260 fast and 232 slow responses. In the risk category, there were five participants, with 153 fast and 167 slow responses. The EEG signal was filtered using a fourth-order Butterworth filter to remove the power line and other noises. The cut-off frequency used ranged from 4 to 40 Hz. The process continues with Independent Component Analysis (ICA) to analyze and remove artifacts such as body movements, eye blinks, and other noise components [26].

The clean EEG signal was then converted using a topographic process to obtain a two-dimensional (2D) image. One-dimensional EEG signals were converted to two-dimensional data using a topographic map. The converted data are shown in FIGURE 6. The darker the area of the cortex, the higher the activity. The topographic map also shows the electrode montage for the 10-20 systems.

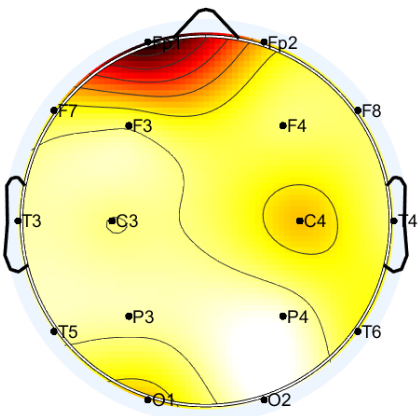


FIGURE 6. Example of EEG Signal Ploted in Two Dimension

D. BUTTERWORTH BANDPASS FILTERING

The raw EEG signals contained significant noise, including components from muscle activity, power line interference, and eye movement. To reduce unwanted frequency components and eliminate noises, a Butterworth bandpass filter was applied to the EEG signals. The Butterworth filter was used is a fourth-order Butterworth filter. A fourth-order Butterworth filter was chosen because it has a more linear response compared to other filters. The cutoff frequencies used are 4 to 40 Hz. Frequencies below 4 Hz were eliminated as they are considered noise, and the frequencies within the chosen range help to reduce power line interference at frequencies of 50 to 60 Hz [27]. The general transfer function $H(s)$ of a Butterworth filter is given by Eq. (1), where ω_c represents the cutoff frequency, and n is the order of the filter [28].

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

For a bandpass Butterworth filter, the transfer function is required combining both lowpass and highpass characteristic. The transfer function for a bandpass Butterworth filter is represented using Eq. (2), where ω_L is the lower cutoff frequency, and $\omega_H$is the upper cutoff frequency that needs to be converted from Hz to radians per second using equation (3) and equation (4).

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

$$\omega_L = 2\pi \times lowcut \tag{3}$$

$$\omega_H = 2\pi \times highcut \tag{4}$$

E. INDEPENDENT COMPONENT ANALYSIS (ICA)

Independent Component Analysis (ICA) is a common step in signal processing used to detect and eliminate noise components, including body movements and eye blinks, which can persist in electroencephalogram (EEG) signals despite prior filtering [26],[29],[29]. This study used EEGLAB, a MATLAB application frequently employed for ICA. EEGLAB offers a broad range of functionalities including signal filtering, ICA, and signal energy visualization. During ICA, the activities in each signal channel were randomly sampled and analyzed [31][30]. Although variations in ICA outcomes between different devices are possible, they generally have a negligible effect on the final signal analysis results.

ICA used statistical method to transform an observed multidimensional random vector into components that are statistically independent from each other as possible. The mathematical formulation of ICA involves several key steps and can be expressed using Eq. (5), and S is the source of signal matrix that is represented using Eq. (6). Where a, b, c, and d are the mixing coefficients. The goal of ICA is to estimate both A and S given X such that the components in S are as statistically independent from each other as possible [31].

$$X = \begin{pmatrix} X_1 \\ X_2 \end{pmatrix} = \begin{pmatrix} as_1 + bs_2 \\ cs_1 + ds_2 \end{pmatrix} = \begin{pmatrix} a & b \\ c & d \end{pmatrix}\begin{pmatrix} s_1 \\ s_2 \end{pmatrix} = As \tag{5}$$

$$S = \begin{pmatrix} s_1 \\ s_2 \end{pmatrix} = \begin{pmatrix} (s_{11}, s_{12}, \dots, s_{1N}) \\ (s_{21}, s_{22}, \dots, s_{2N}) \end{pmatrix} \tag{6}$$

F. MOBILENET V2

MobileNetV2 is a standout choice for feature extraction in object detection and segmentation. MobileNetV2 introduces linear bottlenecks and inverted residuals to better preserve information resulting a superior performance over MobileNetV1 in feature extraction while delivering a 35% boost in processing speed without compromising accuracy [32]. Originally designed for deployment on resource-constrained devices, MobileNetV2's architecture capitalizes on depth-wise separable convolutions to build lean and efficient neural networks. Its versatility in deep learning applications is evident in its adept management of low-dimensional inputs, reduction in computational demands, and ability to maintain high accuracy while conserving memory resources. This combination of speed, accuracy, and resource efficiency solidifies MobileNetV2 as an exceptional option for a wide range of deep learning tasks [9].

FIGURE 7 shows the model construction process, MobileNetV2 serves as the foundational model, supplemented with a GlobalAveragePooling2D layer for feature aggregation, followed by a dense layer incorporating the Rectified Linear Unit (ReLU) activation function, effectively mitigating overfitting [9]. The output layer of the model features sigmoid and softmax activations for binary classification. To optimize the training, the Adam optimizer was chosen with a learning rate of 0.0001, and the sparse categorical cross-entropy (SCCE) loss function was utilized for its ability to generate category-matching indices [33]. Throughout the training, the model performance was assessed using the accuracy metric.

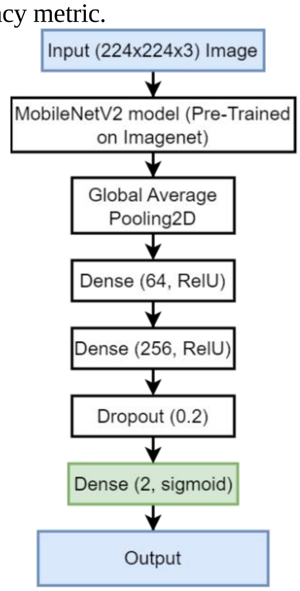
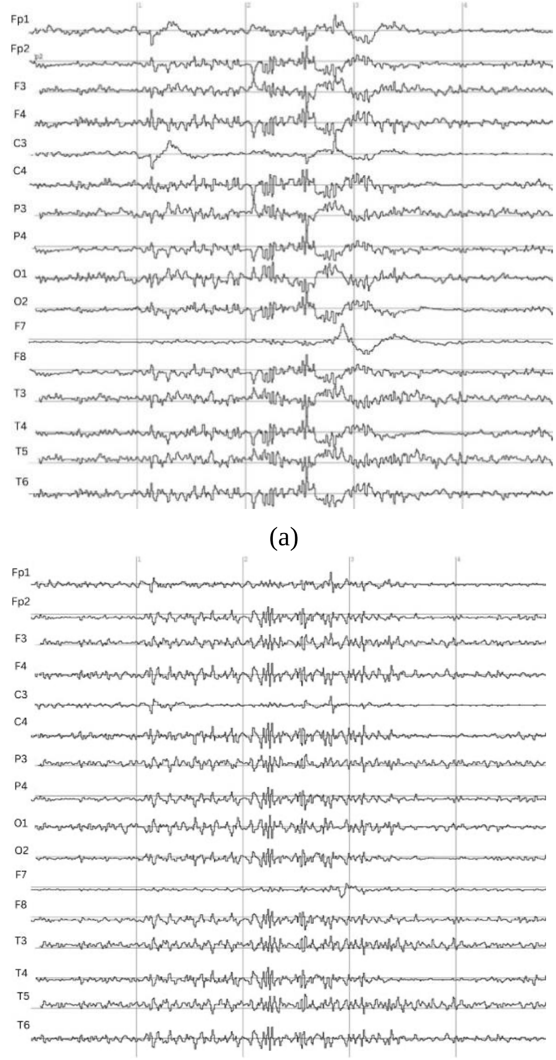


FIGURE 7. The Architecture of MobileNetV2 Model

III. RESULT

The recorded data split into two categories "Normal" and "Risk" based on the classification from Psychologists. Participants in the "Normal" category were those who had never been involved with drugs. While the "Risk" category is those who was involved with drugs themselves or have relatives who have had such involvement. Each category is then divided into "fast" and "slow" response based on the response in pressing the space bar. For a response below 0.5s it is considered fast while the other is slow.



(a)

(b)

FIGURE 8. EEG Signal (a) Before Filtering; (b)After Filtering

A. FILTERING USING BUTTERWORTH

FIGURE 8 shows the pre-filtered signal contains significant noise and the EEG signal that has undergone filtering. Noise is present in the brain activity signal before filtering and includes components from other sources and eye-related components. One of the main objectives of using a Butterworth filter is to reduce unwanted frequency components from a signal with the aim of eliminating such noise. The use of a Butterworth filter can help eliminate noise components, such as eye movements. While noise components in the signal can be reduced, some residual noise may remain in the EEG signal data, necessitating the use of Independent Component Analysis (ICA) to analyze and eliminate components in specific channels [26].

B. NOISE COMPONENT REMOVAL

FIGURE 9 shows the differential between hat noise components still exist in the EEG signal. These noise components are present in channels five and six. However, these noise components cannot be eliminated using filters. These noise components may originate from the EEG recording equipment or recording equipment [34]. The values of these components were determined using the Independent Component Analysis (ICA) method. Using the ICA method, each EEG channel was analyzed to obtain its respective components. In addition, the ICA can eliminate unwanted components from each channel. FIGURE 10 shows the EEG signal after component removal using ICA, the brain activity in the EEG signal increased. Several channels experienced changes in the energy component values. By removing the noise channels, the EEG signal was detected as brain activity in each channel.

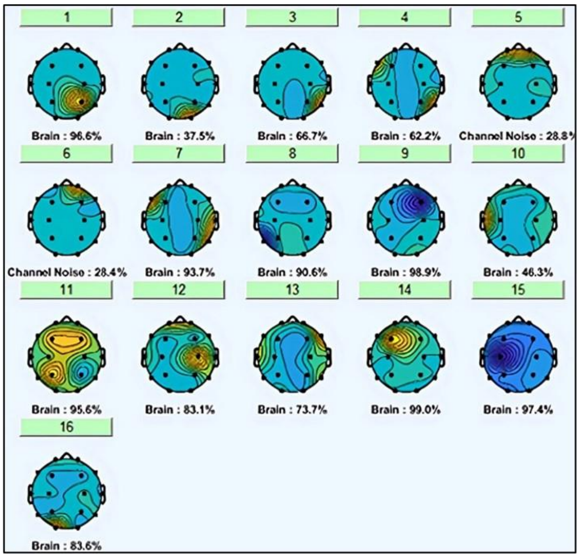


FIGURE 9. **Brain Activity EEG Signal After Filtering**

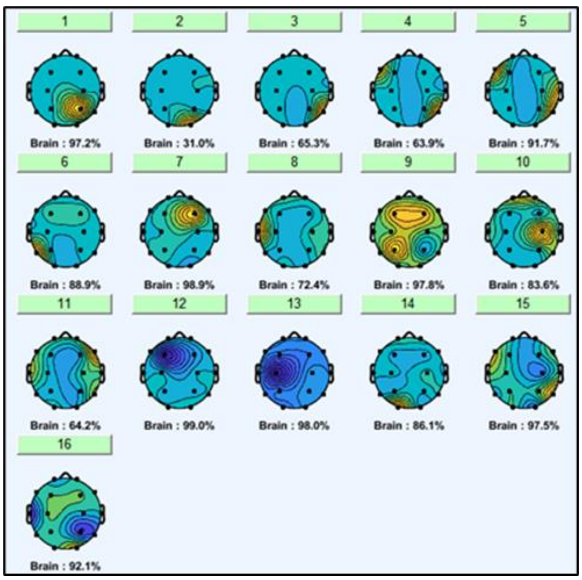


FIGURE 10. **Brain Activity EEG Signal After Removing Components Using ICA**

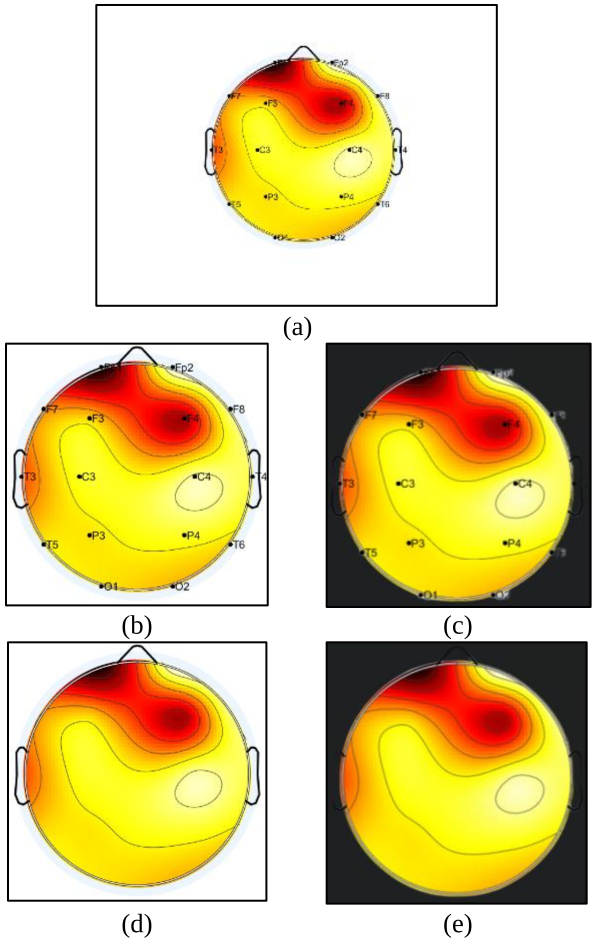


FIGURE 11. **Testing Sample for Each Scenarios: (a) First Scenario;(, (b) Second Scenario; (c) Third Scenario; (d) Fourth Scenario; (e) Fifth Scenario.**

C. TESTING SCENARIOS

The two-dimensional conversion method employed involves the normalization of the energy values of the EEG signal. Recorded EEG signals were segmented for each session. The EEG signal plotting method utilizes the "*topoplot*" function, which requires the location of each used channel to be specified. During the testing process, the dataset was plotted into five different datasets. In this study, five testing scenarios were employed for both the normal and at-risk participants as shown in FIGURE 11. The first scenario utilized the original dataset without cropping while still including electrode information. The second scenario involved cropping the dataset in white areas while retaining electrode information. In the third scenario, the dataset had white areas removed (made transparent), yet it preserved the electrode information. The fourth scenario included a dataset with cropped white areas and excluded the electrode information. Finally, the last scenario used a dataset with white areas removed (made transparent) and did not include electrode information.

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D. NORMAL PARTICIPANTS

The data subjected to detection were two-dimensional EEG energy plotting data that had undergone preprocessing from participants categorized as normal. The data fell into the categories of fast and slow (TABLE 2). There were seven healthy participants, with a total of 260 fast and 232 slow data. The deep learning model used to process normal participants utilizes the MobileNetV2 architecture with a "Sigmoid" dense layer activation. The data were divided into 369 for training, 79 for validation, and 44 for testing, without augmentation (TABLE 3). The hyperparameters used included the Adam optimizer, learning rate of 0.0001, 20 epochs, and batch size of 32.

TABLE 2.
Testing of Normal Participants

Data Testing						
Scenario	Accuracy			Loss		
	Train	**Valid**	**Test**	**Train**	**Valid**	**Test**
1	0.86	0.92	0.84	0.33	0.30	0.39
2	0.88	0.81	0.86	0.31	0.41	0.36
3	0.89	0.74	0.84	0.27	0.44	0.37
4	0.88	0.89	0.79	0.28	0.34	0.46
5	0.90	0.83	0.77	0.25	0.33	0.44

TABLE 3
Average Value of Each Scenario in Normal Participants

Average Value±Standard Deviation						
Scenario	Accuracy			Loss		
	Train	**Valid**	**Test**	**Train**	**Valid**	**Test**
1	0.828± 0.048	0.821± 0.019	0.646± 0.187	0.412± 0.915	0.821± 0.019	0.608± 0.100
2	0.819± 0.0762	0.726± 0.0428	0.839± 0.026	0.414± 0.103	0.493± 0.056	0.391± 0.054
3	0.812± 0.073	0.774± 0.028	0.664± 0.153	0.423± 0.097	0.463± 0.051	0.565± 0.098
4	0.827± 0.063	0.879± 0.035	0.822± 0.166	0.390± 0.099	0.377± 0.06	0.350± 0.241
5	0.802± 0.090	0.781± 0.049	0.886± 0.121	0.421± 0.118	0.486± 0.068	0.175± 0.137

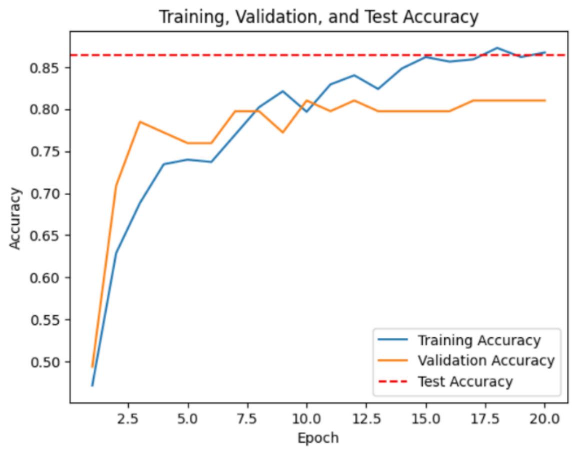

FIGURE 12. **Accuracy Graph for Normal Participants**

From the five experiments conducted, the second experiment yielded the most satisfactory accuracy in classifying the 'fast' and 'slow' categories, as shown in the confusion matrix in TABLE 4. In the second experiment, the data was divided into 42 data with the 'fast' label and 37 data with the 'slow' label, with a total of 79 two-dimensional data analyzed. These numbers were derived from the division of the two-dimensional data for the testing process. The results from the confusion matrix indicate that in the 'fast' class, 31 data points were correctly predicted, whereas 11 data were predicted as 'slow'. In the 'slow' class, 33 data points were correctly predicted by the system, whereas four data were predicted as 'fast'.

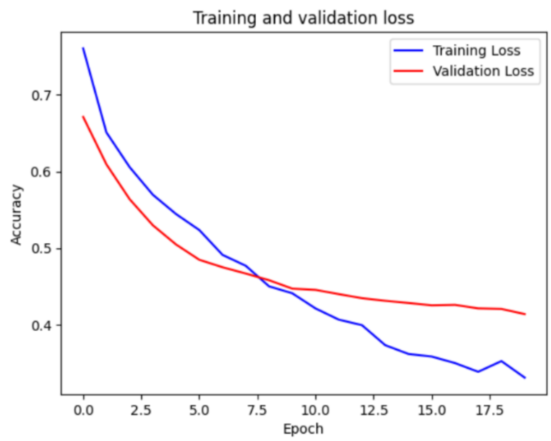

FIGURE 13. **Loss Graph for Normal Participants**

TABLE 4.
Confusion matrix for Normal Participant

True \ Predicted	Fast	Slow
Fast	31	11
Slow	4	33

E. RISK PARTICIPANTS

In the testing, the dataset used consisted of response times from participants categorized as "at-risk" for the words "Narkotika" and "Napza" Napza'. The data were derived from five participant subjects, with a total of 153 data points for the "fast" category and 167 for the "slow" category. The deep learning model used in this test was the MobileNetV2 architecture with the Softmax activation function in the dense layer. The data were split into 240 for training, 52 for validation, and 28 for testing, without augmentation. The selected model used the Adam optimizer with a learning rate of 0.0001, ran for 20 epochs, and used a batch size of 32.

The results from TABLE 5 and TABLE 6 shows that scenario 2 has the highest accuracy, as presented in FIGURE 14 and FIGURE 15**Error! Reference source not found.**. Compared to the first scenario, which represents the original plot of the EEG signal, the second scenario demonstrates the impact of cropping white areas and including electrode information. This results in increased accuracy and reduced loss during training, validation, and testing. The wider white areas in the first scenario cause the architecture to learn more features that are not related to the 2D representation of EEG signal. Additionally, when datasets with the background removed or without electrode information were used, there was a decrease in accuracy and an increase in loss. This is because removing the background also removes some EEG signal information, and there may be instances where the background is not entirely removed.

TABLE 5.
Testing of Risk Participants

Data Testing						
Scenario	Accuracy			Loss		
	Train	**Valid**	**Test**	**Train**	**Valid**	**Test**
1	0.80	0.82	0.75	0.31	0.43	0.44
2	0.89	0.84	0.85	0.28	0.42	0.43
3	0.86	0.78	0.75	0.33	0.47	0.47
4	0.87	0.82	0.78	0.31	0.39	0.44
5	0.88	0.78	0.75	0.31	0.42	0.44

TABLE 6
Average Value of Each Scenario in Risk Participants

Scenario	Accuracy			Loss		
	Train	**Valid**	**Test**	**Train**	**Valid**	**Test**
1	0.775± 0.09	0.765± 0.050	0.785± 0.124	0.481± 0.101	0.555±0. 48	0.357± 0.145
2	0.800± 0.076	0.801± 0.047	0.821± 0.087	0.446± 0.106	0.483±0. 056	0.444± 0.092
3	0.740± 0.105	0.712± 0.085	0.785± 0.2	0.522± 0.122	0.563±0. 084	0.494± 0.196
4	0.770± 0.092	0.798± 0.031	0.750± 0.169	0.504± 0.081	0.478±0. 065	0.473± 0.169
5	0.780± 0.079	0.783± 0.035	0.785± 0.066	0.461± 0.093	0.479±0. 048	0.446± 0.096

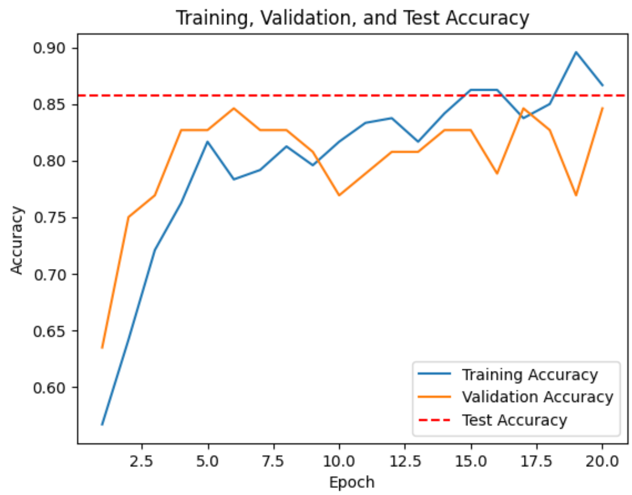

FIGURE 14. **Accuracy Graph for Risk Participants**

Among the five data experiments, the second yielded the most satisfactory accuracy in classifying the 'fast' and 'slow' categories, as shown in the confusion matrix in TABLE 7. In the second experiment, the data were divided into 25 fast-labeled and 27 slow-labeled data, with a total of 52 two-dimensional data points analyzed. This number was obtained from the partitioning of two-dimensional data for the previous training process. From the prediction results, eight data points were incorrectly predicted. These eight data points include one data point that should have been predicted as 'slow' but was predicted as 'fast', and seven data points that should have been predicted as 'fast' but were predicted as 'slow'.

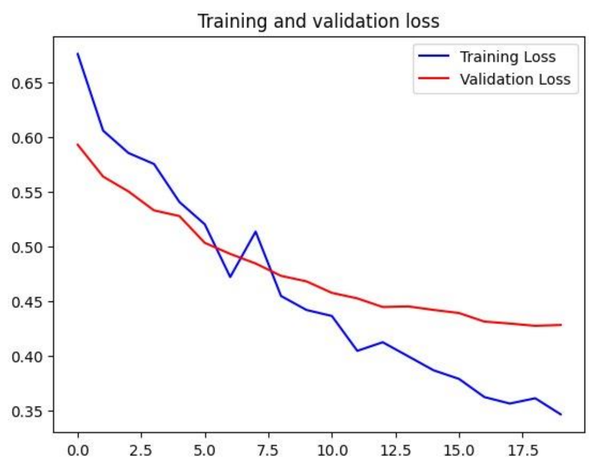

FIGURE 15. **Loss Graph for Risk Participants**

TABLE 7.
Confusion Matrix for Risk Participant

True	Fast	18	7
	Slow	1	26
		Fast	Slow
		Predicted	

V. DISCUSSION

This study leverages the Go/No-Go Association Task (GNAT) to identify narcotic abuse tendencies among adolescents by using 2D EEG signal analysis. The MobileNetV2 architecture achieved highest accuracies of 0.86 for normal and 0.85 for risk categories, highlighting its efficiency in processing neuropsychological data. Using 2D EEG signal representation offers a richer and more detailed view of neural responses compared to traditional 1D data. Cropping the white area on the 2D data while maintaining electrode information minimizes noise and unnecessary features, allowing the architectures to focus more on relevant data. This deep learning approach captures subtle variations in brain activity, which are critical for early detection of drug abuse tendencies.

This study aligns with previous research utilizing MobileNetV2 for processing 2D EEG images. For instance, the study by Fussner et al. [37] demonstrated the effectiveness of MobileNetV2 in classifying 2D EEG images for distinguishing non-epileptic from epileptic seizures, achieving highest accuracies of 87.3%. Similarly, research by Sengur et al. [38] showed that MobileNetV2 achieved high accuracies ranging from 96.1% to 99.6% in identifying human emotions from EEG images. These studies highlight MobileNetV2's robustness in handling complex biomedical data, reinforcing our finding on its suitability for detecting narcotic abuse using EEG images. Furthermore, the transition from 1D to 2D EEG signal representation has been proven to improve accuracy. This is supported by studies such as Yang et al. [11] and Wang et al. [12] using SEED dataset. Yang et al. used 1D EEG signals, achieving 84.21% accuracy, whereas Wang et al. improved accuracy to 90.59% by converting the signal into a 2D representation. Similar trends were observed in motor imagery classification, with Kanoga et al. [13] achieving 87.6% accuracy with 1D EEG signals, while Tanvir et al. [14] reached 97.7% accuracy by converting time-series EEG signals into 2D images using the BCI Competition IV dataset. This study's 2D EEG signal processing approach mirrors these results, demonstrating enhanced classification performance in the context of drug abuse detection.

Despite the promising results, there are several limitations that must be acknowledged. First, the sample size of 12 participants is relatively small, which may affect the generalizability of the findings. Future studies should include a larger and more diverse sample to validate these results. Additionally, while the 2D EEG signal representation provides detailed neural information, it also demands significant computational resources, which could be a barrier for broader implementation.

The implications of this study are multifaceted. From a clinical perspective, the high accuracy of MobileNetV2 in classifying narcotic abuse tendencies suggests that this method could be integrated into early intervention programs, aiding psychologists and educators in identifying at-risk adolescent. The introduction of TUNDA dataset offers a valuable resource for future research, encouraging further exploration into EEG-based drug abuse detection.

VI. CONCLUSION

In this study, VEPs analysis was performed on the recorded EEG signals to examine participants' responses to stimuli related to narcotics. The EEG signal was converted into a 2D object in the form of a topological plot for each channel that represented the VEPs response. There were seven participants in the normal category, with 260 fast responses and 232 slow responses. There were seven healthy participants (normal), with a total of 260 fast and 232 slow data. The MobileNetV2 architecture yielded the best classification results under scenario two, achieving a test accuracy of 0.86 and test loss of 0.36. In the risk category, there were five participants, with 153 fast and 167 slow responses. The deep learning model used to process the data participants utilized the MobileNetV2 architecture and obtained the best classification results using scenario two with a test accuracy of 0.85 and a test loss of 0.43. The data risk category was obtained from five risk participants, with 153 data points for the "fast" category and 167 for the "slow" category. This characteristic can be used for the early detection or prevention of narcotic abuse. Further validation is needed to increase the accuracy of the dataset. It is hoped that the results of this preliminary research will help medical practitioners or psychologists in the early detection or prevention of narcotic abuse. Future research could focus on several key areas to strengthen these findings. First, expanding the sample size by including more participants from diverse social and cultural backgrounds will enhance the generalizability of the study's results. Additionally, exploring more efficient methods for 2D EEG signal representation could help reduce computational resource demands without sacrificing accuracy. Developing more efficient deep learning models that can be implemented on devices with limited computational power is also crucial for broader clinical application.

DATASET

The dataset is available to the public in the Dataverse repository of Telkom University via the link: https://doi.org/10.34820/FK2/GW8JIV.

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