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Effect on signal magnitude thresholding on detecting student engagement through EEG in various screen size environment

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ABSTRACT

In this study, a new method was developed to detect student involvement in the online learning process. This method is based on convolutional neural network (CNN) as a classifier with an emphasis on the preprocessing process combined with a new feature in the form of signal magnitude area (SMA) thresholding. In this study, the data used as training data is a public dataset that emphasizes the decomposition of electroencephalography (EEG) signals into individual signal processing. Twenty subjects were taken to be used as test data, with each subject watching online learning lectures in the field of computer science on three different devices, either with a flat screen, a curved screen or a smartphone screen that is smaller than two standard computer monitors. Based on the study's results, it is known that the change in screen size is inversely proportional to the level of student attention, the smaller the screen, the lower the student's attention. For classification results, the model equipped with SMA thresholding outperformed the standard classifier by 8.33% with a test set of 20 people.

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1. INTRODUCTION

In the face of the COVID-19 pandemic, a series of government regulations were issued to mitigate the impact of this virus in the daily lives of the Indonesian people. Minister of Education decree No. 4 of 2020 states directives that make online learning mandatory for schools and tertiary institutions in Indonesia [1]. This considerable change in teaching and learning paradigm raises questions in academia. Although research discussing the effectiveness of online learning has been implemented before [2], [3], but on a large scale like this it hasn't been done much [4], not only in terms of education but also many preliminary studies conducted in the health sector, especially in the field of eye health [5] and ergonomics [6], [7]. Given that online learning, which is the primary way of teaching and learning during this pandemic, requires a very large screen time compared to normal conditions, the diverse profiles of Indonesian students make the tools used in carrying out this process an interesting variable to study. A similar study has been conducted, but the scope is in the work environment and was carried out in Korea [8]. In several fatigue studies that are mostly done in the world of transportation [9]-[14], on screen time in education has not become a research problem that many people do [15]. However, in several previous studies have indeed been implemented on human-computer interaction, the application of brain waves has not become a standard parameter to be used as an aspect of assessing the conditions that occur, although in several studies the brain wave parameters show a more stable and objective value and can be tested by accurate than other biological parameters [16]-[18]. Brain waves are a test parameter that is often used in defense-based research [19], [20], research in the branch of advertising science as well as research in the branch of psychology [21]-[25]. This study utilizes what has been done previously by researchers at Carnegie Mellon University which has provided a data set that measures the level of engagement and student focus on an online learning activity [26]. However, in this study, no good data cleaning was carried out, and no statistical tests were carried out on the data before transforming it into a process tensor in the classifier. In this study, each research subject will be compared with all available data to make this research more objective with the introduction of a thresholding system based on the signal magnitude area (SMA) method so that the classifier obtained in the end will be more sensitive to local overfitting than the classifier, which does not use a thresholding system which is strengthened by data from previous studies with almost similar experiments [27]. In addition to measuring the effectiveness of using SMA, this study will also compare the effectiveness of using different screen sizes in online learning. Research related to the effectiveness of screen size in learning has been done [28]-[30]. However, in this case the researcher will use brain wave parameters and self-assessment to determine the participant's level of focus when using the three different screen sizes.

2. METHOD

2.1. Research design

In this study, the author focuses on the effect of screen size on the level of attention and understanding of students in distance learning. In this research design, si classification uses a combination of SMA which has been modified by combining it with the convolutional neural network (CNN) classifier with multiple input variables. Figure 1 shows the location of the sensors that can be observed in brainwave data retrieval. The data retrieval results using these sensors will be processed to obtain brainwave signals affecting student focus. In general, this experiment is divided into 4 major phases, namely preprocessing data, converting data into SMA-scale data, then converting the data into tensors for processing on the CNN network, and the last stage is classification using a multivariable CNN classifier using deep learning methods. Preprocessing is the stage where the data is cleaned of artifacts and noise using the z-score averaging method to be processed in the next phase. Then the next step is to process the data into a signal magnitude scale by taking the median of each data and comparing it with a data point. The next step is the data is prepared to be entered into a CNN-based artificial neural network after the conversion is complete then the data is forwarded to a CNN-based classifier that has been trained previously by public data that focuses on student engagement and focuses attention on the content presented on a digital screen [26].

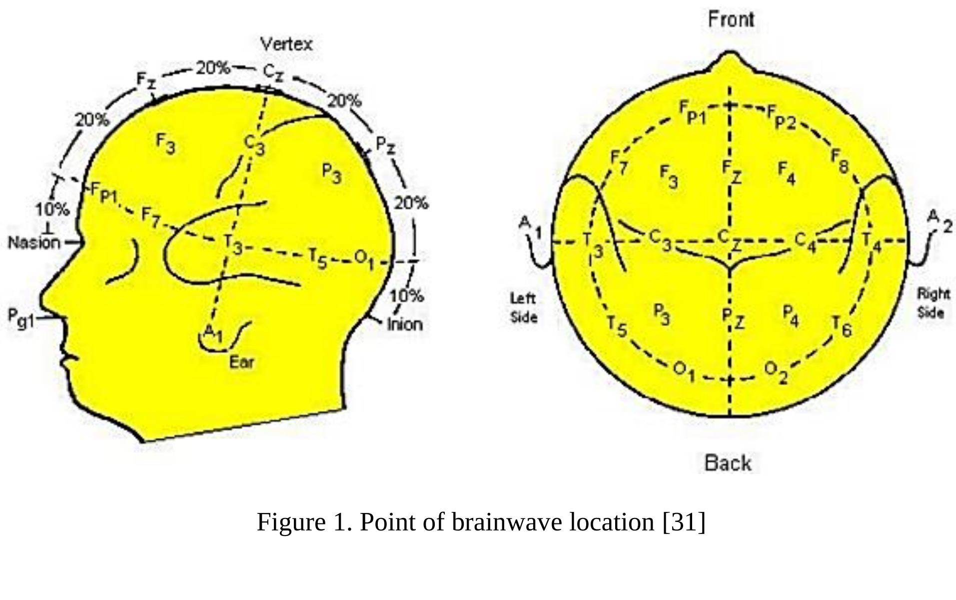


Figure 1. Point of brainwave location [31]

In the next process, the classifier will classify the participants into the not-engagement class and the focused (engaged) class. In the final process, the model will be tested with a parameter matrix which includes classical methods such as sensitivity accuracy, which will be combined with an output comparison where the predictions of a system will be compared with the original specifications and later, the general system performance will be evaluated according to the data in the matrix. Figure 2 shows the steps for classifying a person's attention level using this experiment.

Figure 2 shows the steps in proving the method offered, the first step in this research is to collect brain wave data. This data can be obtained from an electroencephalography (EEG) tool that can record the participants' brain waves and then be normalized using z-score normalization. To remove the noise from the brainwave data, a denoising process was carried out using the SMA method to obtain the allowable data value for analysis. This research focuses on the preprocessing process, which needs to be addressed in previous research and also uses public data tested by previous researchers [32], not using private data whose data validity may be doubted. The normalized data is collected in a feature matrix, and the matrix is transformed into data that matches the CNN features to be used. The data will later be tested using a modified model using public data. This model recognizes two states, namely a state of comfort and a state of discomfort. The class will predict one of the two outputs to be used as a reference in evaluating the performance model. Table 1 is an example of the results of recording brain waves using EEG. From the results of these recordings, the system can record several attributes of the brain waves in the form of attention level, raw data, delta, theta, alpha, beta, and gamma signals.

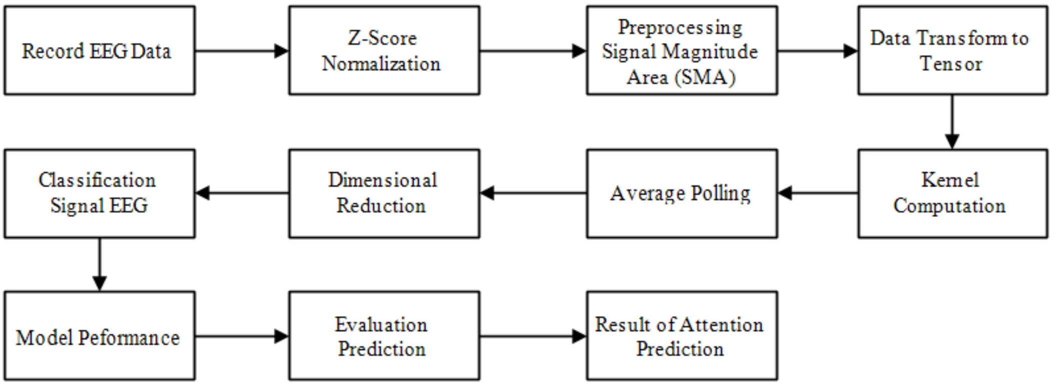


Figure 2. System overview

Table 1. Sample of brainwave data

No	Att	Raw	Delta	Theta	Alpha	Beta	Gamma
1	77	612	1168234	76559	17671	31863	5930
2	61	650	1000755	284199	106613	137788	44498
3	61	555	1000755	284199	106613	137788	44498
4	69	359	1397841	83854	13089	39550	12335
5	69	42	1397841	83854	13089	39550	12335
6	70	-6	220810	42100	10811	6305	1055
7	81	33	882279	446036	200258	19463	12986
8	81	213	882279	446036	200258	19463	12986
9	88	222	538825	90035	248874	10521	5208
10	88	-43	538825	90035	248874	10521	5208
12	90	266	486405	532454	148791	21272	4584

Data format:

Att : attention level measured by neurosky algorithm
Raw : unfiltered EEG brainwave signal
Delta : signal delta EEG brainwave
Theta : signal theta EEG brainwave
Alpha : signal alpha EEG brainwave
Beta : signal beta EEG brainwave
Gamma : signal gamma EEG brainwave

In the final stage, the data in this study will be evaluated and tested based on a confusion matrix as a test method that will produce system accuracy, focus comparisons when using different devices, and comparisons of the CNN method without preprocessing and using SMA preprocessing. To observe what signals, need to be taken to observe student focus, Figure 2 is the condition of a person with a signal recording range from 0 to 40 Hz. Based on Table 2, it can be seen that the characteristics of the data tested in this study where the data will be parsed according to their respective dimensions, some of which symbolize the SMA index, which represent the brain waves that have been divided according to the EEG power band standard, namely four types of alpha beta delta waves and a scale property attention results from device manufacturers and they will be compared with self-assessment scales made by participants on the training dataset.

Table 2. Characteristics of EEG brain waves [33]

Brain wave	Frequency range (Hz)	Occurrence
Delta	0–4	Condition sleep
Theta	4–8	Condition going to sleep
Alpha	8–13	Condition relax, calm, thinking
Beta	15–40	Condition focus, alert, mental work, anxiety including

2.2. Preprocessing EEG

In the initial step, the dataset that will be used as training data will be normalized. Figure 3 is the histogram of the dataset that will be used as system training data. Figure 3 is a histogram of the brainwave dataset that will be used as training data, where Figure 3(a) shows the results of the attention level data recording, Figure 3(b) shows the raw data from the brainwave recording while Figures 3(c)-(f) shows the recorded signal to be observed for the training data.

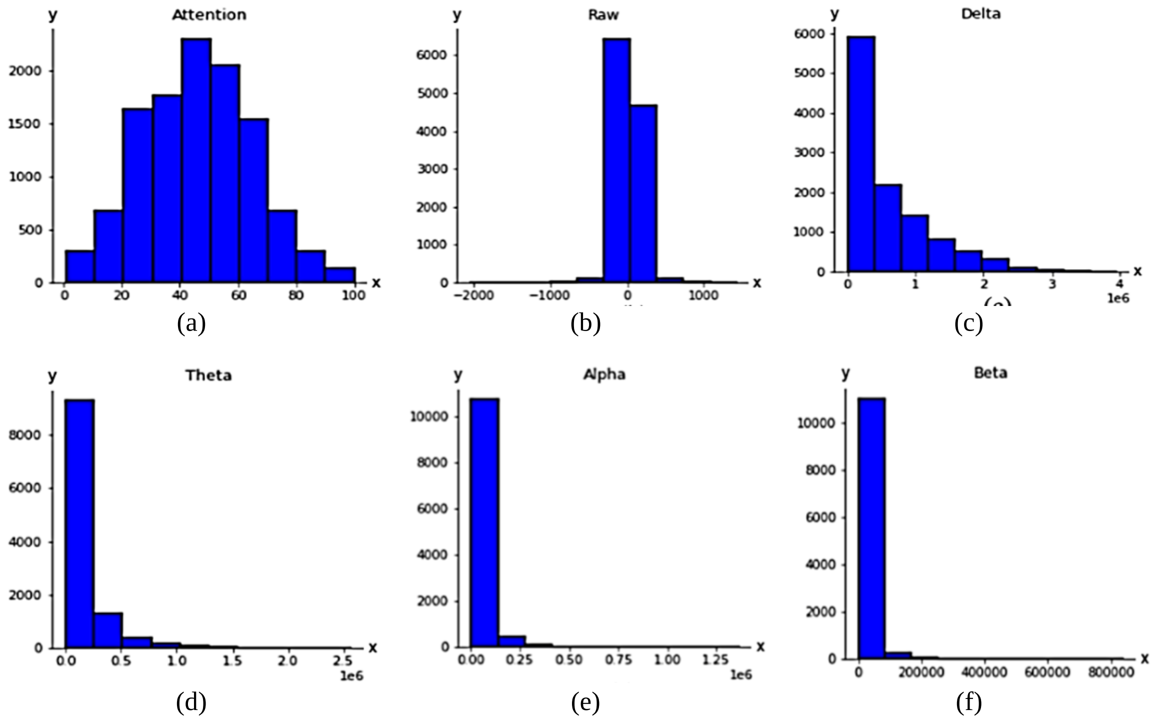


Figure 3. Histogram of features dataset (a) attention level, (b) dataset raw data, (c) delta signal, (d) theta signal, (e) alpha signal, and (f) beta signal

The initial and most crucial part of this research is retrieving data from brain waves and ensuring that the data taken is ready to be analyzed and included in the classifier. In this process, the normalization process will be implemented using the z-score method with the following formula [34].

$$Z = \frac{X-X}{SD_x} \quad (1)$$

After normalizing the data, there will be some standardized data using the z-score calculation, and Figure 4 is the histogram of the normalized data using the z-score calculation. Data normalization is making several variables have the same range of values, none of which are too large or too small, to make statistical analysis more straightforward. The normalization method used in this study is the z-score, the standard score. The essence of this technique is to transform data from values to a broad scale where the mean is zero, and the standard deviation is one. The results of normalization are shown in Figure 4, where Figure 4(a) shows the histogram of normalized attention level results, Figure 4(b) shows the results of normalization of raw data, and Figures 4(c)-(f) shows the results of normalizing the EEG signal.

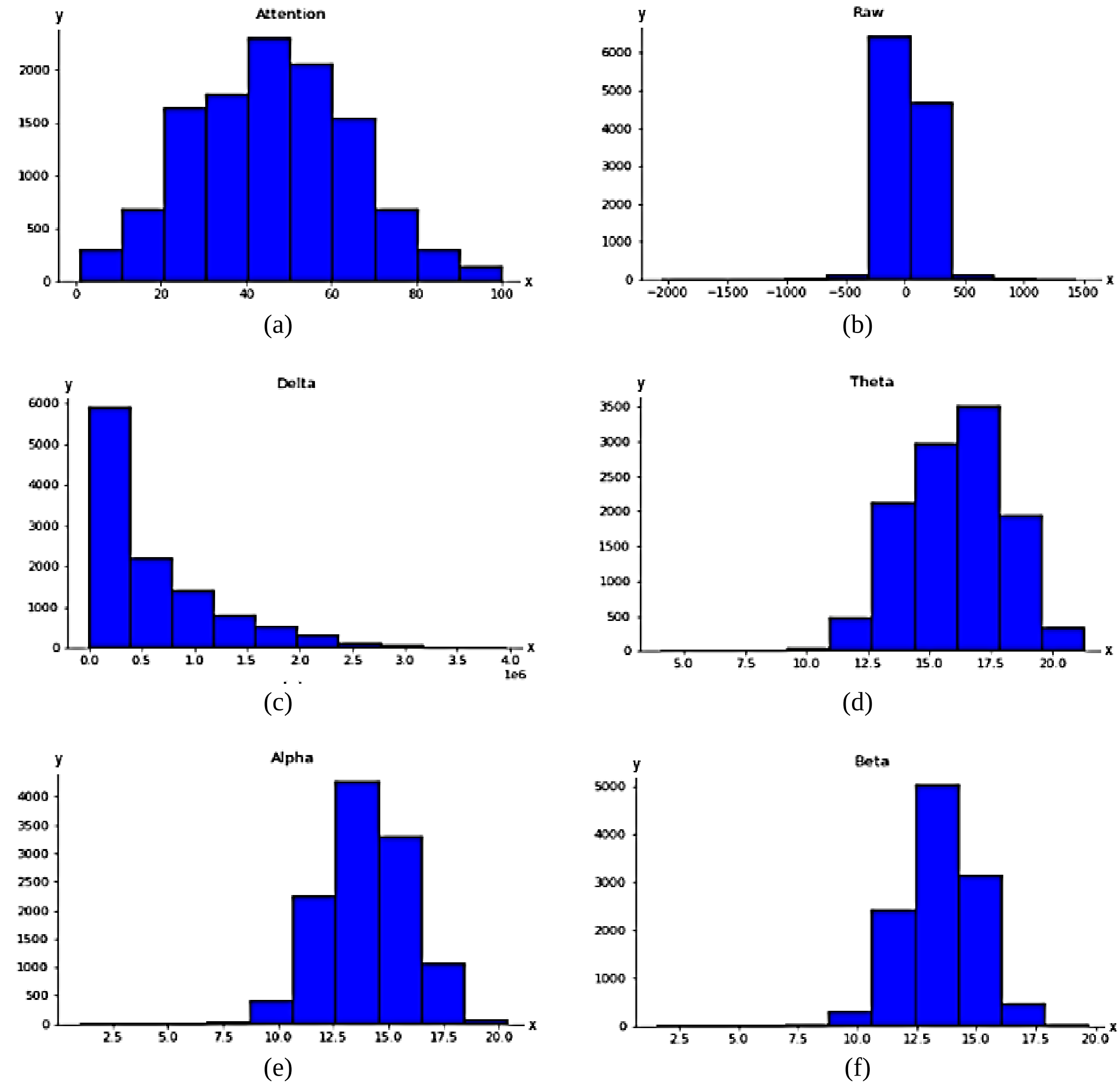


Figure 4. Histogram of data (a) attention level after normalization, (b) raw data after normalization, (c) delta signal after normalization, (d) theta signal after normalization, (e) alpha signal after normalization, and (f) beta signal after normalization

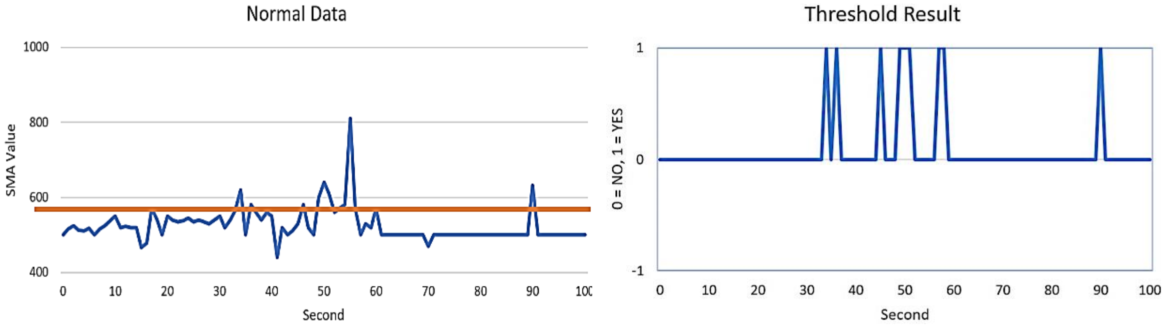
After the normalization process is carried out using the z-score method. The results of brain wave normalization will be processed using the SMA method to detect outline data so that the data obtained avoids overfitting. The following is the formula used for preprocessing using the SMA method [33].

$$\text{SMA} = \sum_{i=1}^{N-1} \left| x_{(i+1)} - x_i \right| \quad (2)$$

Before entering the machine learning process, the normalized data must first have a threshold so that noise does not occur during machine learning processing. This method will later adjust the characteristics of the data with machine learning methods and the characteristics of the single band EEG tool used in this study. The determination of the threshold or threshold in this study uses the following equation.

$$\text{EEGThreshold}_{(x)} = AVG\left(\text{SMAs}_{(x)}\right) + \text{STD}\left(\text{SMAS}_{(x)}\right) \quad (3)$$

In calculating the threshold using the formula above, the researcher will determine the threshold for brain wave data permitted to be processed using the CNN method. The threshold results from this calculation are illustrated in Figures 5(a) and 5(b) with the threshold used as a natural evaluator to compare individuals and populations. Figure 5(a) shows the recorded brain waves divided using the SMA scale to produce groups above and below the threshold, while Figure 5(b) shows the allowable threshold using the SMA scale. The use of the SMA method in this study aims to standardize the signals obtained to improve the accuracy of the test results.



(a) (b)

Figure 5. Example of the frequency of brain wave recordings (a) normal data before the threshold process and (b) results threshold using the SMA method

2.3. EEG classification with CNN

CNN is a method derived from the development of the multilayer perceptron (MLP) for processing two-dimensional data [35]. Figure 6 is a design for applying the CNN method to classify recorded brainwave signals as focused or out of focus. CNN is a method that was first developed under the name NeoCognitron by a Japanese researcher named Kunihiko Fukushima [36]. The concept developed by Kunihiko Fukushima was later developed by a researcher from the USA on behalf of LeCun. LeCun succeeded in developing CNN's initial model under the name LeNet in research that discussed number and handwriting recognition. The application of the CNN method is getting more and more popular, thanks to the fact that in 2012 Alex Krizhevsky won the ImageNet large scale visual recognition challenge 2012 competition using the CNN method. This further proves the CNN method as the best object classification method in the image, after outperforming other machine learning methods such as SVM [37].

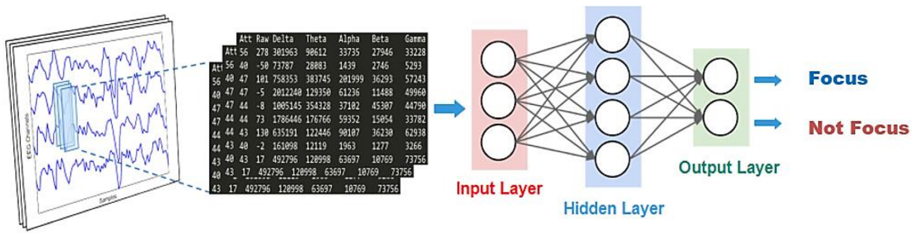


Figure 6. CNN architecture method

2.4. Testing scenario

In this study, testing the proposed method will be carried out on 20 participants. Each participant will be given approximately 10 minutes to watch learning videos related to the introduction of algorithms and programming. In these 10 minutes, the recording duration will only be 5 minutes to reduce data errors at the test's beginning and end. This test will be carried out on each participant using three different devices: a curve screen, a flat screen and a smartphone. In addition to assessing the recorded brain waves, this study will also conduct a self-assessment based on standardized questions with psychological standards. The purpose of this self-assessment is that later there will be two sides to the measurement, which will result in the test results being accountable. Figure 7 is testing documentation when students carry out the online learning process using different types of screens, where Figure 7(a) shows the user using a curve screen, Figure 7(b) using a flat screen, and Figure 7(c) using a smartphone screen.

Figure 7(a) is the process of recording student brain waves during online learning using a curve screen, and you can see the student's head using the tool used to record brain waves. Figure 7(b) shows the process of recording brain waves using a flat screen and Figure 7(c) shows the process of recording brain waves when students use smartphones. The brain recordings from different screens will later be compared to produce which device produces the highest focus when used as a learning medium. Not only comparing, but this study also uses the CNN method to classify attention from brain wave recordings and compares it with the accuracy of the application of the CNN+SAM method when classifying participants' attention levels.

(a) (b) (c)

Figure 7. Brainwave testing and data collection with (a) curve screen, (b) flat screen, and (c) smartphone screen

3. RESULTS AND DISCUSSION

3.1. Testing with different screen scenario

In this study, each participant listened to a lecture on the introduction of algorithms and programming. Each lecture session in this study was conducted for approximately 10 minutes for each module. Each participant was given a different screen for each module to become a random variable in this study. In this test with a duration of 10 minutes, brain wave recording will start from the 5th minute to the 10th minute. This was done to minimize the imperfection of the data because the participants in the first minute currently adapting to the use of the tool. Following the test scenario described, the total number of participants used is 20. Table 3 is a sample of test data that displays the results of 10 participants' brain recordings with different screen types like curved, flat, and smartphone screens. The average results of each difference in screen size used in this study will be presented in Table 4.

Table 3 shows the results of recording user brain waves while watching learning videos with different types of screens: curve, flat, and smartphone, which were observed by recording brain waves and giving a questionnaire in the form of a self-assessment to validate the results of brain wave recording. If you look at it broadly, it may be obscure that the difference in the level of attention of different devices is obvious. To see the effect of the differences in each screen used is presented in Table 4.

Table 4 shows the average user attention level results when using the curve, flat, and smartphone screens. The average value attention level for curved screens is 71, flat screens are 68, and smartphone screens are 65. The results of this attention level are also supported by the results of the self-assessment questionnaire, which is directly proportional to the average attention level results. In general, the results of this test show that the average level of attention when users use curved screen devices is significantly more than flat screens and smartphones. This result is because the large and curved screen makes the user comfortable watching the lessons given it will indirectly increase the user's level of attention.

Table 3. Sample test results with different screen types

Sample user	Screen type	Raw data	Alpha wave	Beta wave	Delta wave	Attention level	Self-assessment of attention
001	Curved	612	11804	74577	12935	75	1
002	Flat	534	22302	28650	12046	75	0
003	Smartphone	33	25023	18700	32025	60	1
004	Flat	650	30609	21250	14027	70	1
005	Flat	507	44000	16500	21250	70	0
006	Flat	-43	57625	17700	23090	76	1
007	Curved	465	33000	51250	24270	78	1
008	Curved	272	17890	72000	13210	80	1
009	Smartphone	80	24020	48730	32025	73	1
010	Smartphone	12	24021	38650	31020	72	1

Table 4. Average test results with different screen types

Number of sample user	Screen type	Average raw data	Average alpha wave	Average beta wave	Average delta wave	Average attention level	Self-assessment of attention
20	Curved	75.56	41383.25	24319.39	605787.35	71	18
20	Flat	73.12	38112.12	23452.78	60782.45	68	16
20	Smartphone	73.06	34235.67	18456.81	61973.65	65	14

3.2. Comparison of CNN classification and CNN+SMA thresholding

In the experiment, the CNN classifier and the CNN classifier combined with the SMA were developed to predict the study's degree of engagement between subjects from brain wave data. The results of predictions and experiments that have been carried out will be compared with the results of each student's self-assessment to find out whether the predictions made by the classifier are correct, and then statistical calculations are carried out, which are used to measure the effectiveness of the model in measuring the level of student involvement. Table 5 is the result of testing the application of the SMA method as preprocessing to classify the level of student engagement when doing online learning.

Table 4 shows the SMA method combined with the CNN method to classify whether the user is focused when given video learning material. Based on tests involving 20 users, it was found that the prediction results given by the system by reading brain waves using the CNN method were smaller than the combination of the CNN and SMA methods. The prediction results from a system that combines the CNN and SMA methods have a smaller prediction error than the CNN method, as evidenced by the answers from the user's direct self-assessment. Based on system testing, it was found that using the CNN method combined with SMA at the preprocessing stage has a higher accuracy value than relying solely on the CNN method, where combining these methods can provide an increase of 8.33%.

Table 5. Comparison of CNN and CNN + SMA method

No	Screen type	Prediction of attention level with CNN		Prediction attention level with CNN + SMA		CNN accuracy (%)	CNN + SMA accuracy (%)
		True	False	True	False		
1	Curved	17	3	18	2	85	90
2	Flat	14	6	17	3	70	85
3	Smartphone	15	5	16	4	75	80
		Average Accuracy				76.67	85

4. CONCLUSION

Based on the study results, adding a SMA as a thresholding method at the preprocessing stage in the development of an engagement detection system in online learning increased the classifier's performance by 8.33%. The results of experiments conducted in this study indicate a correlation between the addition of the SMA index with the addition of the level of attention with a proprietary algorithm produced by Neurosky as a device manufacturer. These results indicate that the potential of the SMA method to be developed as a parameter to calculate brain wave relaxation is work that needs to be explored in further research. In addition, using a curve screen produces a higher attention level value than using flat screens and smartphones in the implementation of distance learning. Education providers can consider it one of the concerns to improve the quality of student learning.

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