**2022 International Conference on Data and Software Engineering (ICoDSE)**



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# PROCEEDINGS OF
## 2022 INTERNATIONAL CONFERENCE ON DATA AND SOFTWARE ENGINEERING (ICoDSE)

ICoDSE 2022

International Conference on Data and Software Engineering

November 2nd- 3rd, 2022 | Denpasar, Bali, Indonesia

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Proceedings of

# 2022 International Conference on Data and Software Engineering (ICoDSE)

Denpasar, Bali, Indonesia

November 2nd - 3rd, 2022

# General Chair's Message

Welcome to the 2022 International Conference on Data and Software Engineering (ICoDSE),

It gives us an immense pleasure to grace all of your presence at this conference. This year marks the 8$^{th}$ occasion of this annual conference, which was started in 2014. Institut Teknologi Bandung as the founder and host of the ICoDSE first organized the conference in 2014 in Bandung. In 2015, the conference was held in Yogyakarta in collaboration with Universitas Gadjah Mada. In 2016, the third conference was held in collaboration with Universitas Udayana in Denpasar, Bali. The following year, the 2017 conference was co-hosted by Universitas Sriwijaya in Palembang. The fifth ICoDSE was co-hosted by Universitas Mataram in Mataram. In 2019, the sixth ICoDSE was held in Pontianak with Universitas Tanjungpura as the co-host. In 2021, after a year of hiatus due to COVID-19 pandemic, we organized the 2021 ICoDSE online in collaboration with Eindhoven University of Technology of the Netherlands and Universiti Teknologi MARA of Malaysia as co-organizers. This year we gladly present the 2022 International Conference on Data and Software Engineering (ICoDSE) as a hybrid conference. This year we return once again to the beautiful island, the pride of Indonesia, Bali, with our respected partner, Universitas Udayana as our co-organizer. As previous ICoDSE, 2022 ICoDSE is technically co-sponsored by IEEE, in particular the Computer Society Indonesia Chapter.

The theme of this year's conference is **"Data Engineering and Software Engineering in the Era of Metaverse"** The 2022 ICoDSE aims to bridge the knowledge between Academia, Industry and Community. This is a forum for researchers, scientists and engineers from all over the world to exchange ideas and discuss the latest progress in their fields. The two-day conference highlights recent and significant advances in research and development in the field of Data/Knowledge and Software Engineering.

This year, we have received 58 submissions from authors coming from 11 countries around the globe, namely Indonesia, Austria, China, Germany, Ghana, Japan, Malaysia, Mexico, South Africa, Thailand, and the United States. All submissions were peer-reviewed by at least 3 reviewers from external reviewers and the program committee, and 29 papers are accepted for presentations.

Finally, as the General Chair of the Conference, I would like to express my deep appreciation to all members of the Steering Committee, Technical Programme Committee, Organizing Committee and Reviewers who have devoted their time and energy for the success of the event, especially our partner Universitas Udayana. We also would like to thank all authors, presenters, and participants for their outstanding contributions to this forum.

It is our sincere wish that this conference would become an exciting meeting place for you to share ideas, knowledge, and wisdom. Finally, we wish you an enjoyable conference.

Wikan Danar Sunindyo
General Chair of 2022 International Conference on Data and Software Engineering (ICoDSE)

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# Table of Content

# Author Index

# Effect of Different Online Learning Screen Sizes During the COVID-19 Pandemic: An EEG Study

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***Abstract*—The COVID-19 pandemic has given rise to a different learning paradigm than before, from offline learning to online learning. This paradigm is, of course, still popularly used today even until the pandemic ends in the future. The learning paradigm in question is the online learning method. Online learning method not only provides convenience for students or educators but also creates problems that are very interesting to observe. One of the variables that become a problem in this learning method is the students' level of focus in online learning because online learning requires a lengthy screen time, and students use different devices. In this study, we will analyze the level of focus of students participating in online learning using smartphones and laptops. The problem with online learning is the different focus conditions due to differences in the use of devices, affecting the delivery of material received by students. The age limit of students used as the research object is 18-20 years. The approach used to analyze this problem is measure the level of focus using a brain wave recorder Electroencephalogram (EEG). As many as 25 students will observe their level of focus when participating in online learning using laptops and smartphones. Based on research conducted, the focus level of students using smartphone devices has an attention level of 54.72% and laptops by 60.80%. Laptop use has a higher level of attention by 5.76% than smartphone use.**

Keywords—Student Focus, Attention Level, Post Pandemic Education, Elektroensefalogram (EEG), Brainwave.

## I. Introduction

The COVID-19 pandemic from the end of 2019 until now has not ended, new variants of this virus keep popping up, which causes people to have to get used to the new habits that are present today both in the education sector, work, and other sectors. During the early days of the pandemic, all teaching and learning processes were abolished to limit the spread of this virus, and after a while the idea emerged to organize online education. This idea is stated in the decree of the Minister of Education Number 4 of 2020 which requires online learning for Indonesian higher education [1]. To overcome the paradigm during the pandemic, schools use online learning methods to make students still able to study comfortably without fear of being exposed to the COVID-19 virus. This online learning method is certainly many questions for academics, both in terms of the seriousness of students, interactions and the effectiveness of this learning method. Although research on the effectiveness of distance learning via the internet has been widely carried out [2], not much has been done on a large scale like this [3], not only in terms of education but also because many previous studies have been conducted in the health sector, especially in the field of eye and eye health ergonomics [4]. The variety of tools used in online learning is a very interesting research topic to observe, judging from previous research that took the case of students' eye health and ergonomics in the implementation of online learning, in this study, observations will be made regarding how students concentrate when doing online learning using tools, the most frequently used are smartphones and laptops based on brain wave observations using an electroencephalogram (EEG). Research that compares the effectiveness of screen sizes in online learning has been conducted but has not touched the realm of analysis using EEG, where the research topic is still in the realm of learning methods and to get the results of effectiveness analysis using different screen sizes, test results are used. [5], [6].

The electroencephalogram itself is a device used to record electrical activity in the brain, where by using standard sensors found on the EEG device, researchers can record several waves such as Alpha, Beta, Delta and Theta. Each brain wave produced will be calculated to be able to draw conclusions about how much concentration of students is when carrying out online learning using different devices. The importance of this research is because, in its application, online learning requires students to always be on screen time during the learning process, where the length of the learning process cannot be said to run in a short time. The average learning process carried out for each session in a university

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environment is 45 minutes. The question that arises from the example case is whether students are still focused on receiving online learning at that time.

Previous case studies between human and computer interactions observed based on brain waves have actually been carried out, and these brain waves have become a commonly used parameter to detect the dynamics of interactions that occur [7], although on several occasions, it has been proven that brain wave parameters tend to be more stable and stable. Of its reliability or can be said to be more tested than other biological parameters. Brain waves are a test parameter that is often used in defence-based research [8], research in the advertising branch of science and research in psychology and psychology. In the early stages of this research, the students will record brain wave signals while learning using smartphones and laptops. The brain wave signals obtained in the early stages will be in the form of band powers. Later, the power bands will be classified based on Alpha, Beta, Delta and Theta signals. After successfully classified, the signal will be normalized and processed to produce the attention value of each student when using smartphones and laptops so that later it will be able to compare how the students' attention differs when carrying out online learning using the two devices. The contribution that the author can give to the next research is that it is hoped that with this research in the future, the education provider can provide input to students or parents of students to recommend learning devices, especially in terms of the type of screen that is suitable for use to support the learning process so that even though learning is carried out online, the focus of students in transfer knowledge given can be maximized.

## II. Related Work

### A. Related Research

Research related to the effectiveness of distance learning via the internet has been done a lot [2]. However, when compared to a large scale, this research model has not been widely carried out [3] because this online learning paradigm only jumped when the COVID-19 pandemic hit the world since 2019 ago. Until now, research related to student learning concentration has not been widely studied using brain wave condition parameters, previous studies have mostly taken cases in the form of qualitative studies from the side of students [2]. In this study, the authors tried to analyze the focus of students' learning by observing brain waves using Electroencephalography (EEG) devices. Many studies using EEG have actually been carried out, but only a few have touched on the world of education, research related to EEG has mostly touched on the realm of fatigue [4], and the most frequent causes of fatigue raised using EEG analysis are cases of transportation fatigue [9], [10], [11], [12]. Based on the lack of focus on student learning cases who were appointed by conducting brain wave analysis, in this study, the researchers wanted to see the effectiveness of the implementation of online learning using the most frequently used tools for online learning.

### B. Electroencephalography

The tool that can be used to read a person's brain waves is an Electroencephalography (EEG) device [13], research using EEG actually became popular in the era after the second world war when it began to find indications that the human brain emits small electrical impulses which can eventually be captured and transmitted read to indicate certain biological symptoms as well as biological activities such as muscle movement and eye movement [14]. The domain that is often detected using EEG is fatigue detection in transportation research, where EEG as a device is used to read human brain waves, study them and draw certain conclusions, as well as make safety devices. In addition to the transportation field, brain wave readings can also be used to see the amount of meditation and concentration level for each user, where the level is by formulating the main signal that the brain wave reader can record. The standard signals that can be extracted from the raw brain wave data produced are Alpha, Beta, Delta and Theta signals [15].

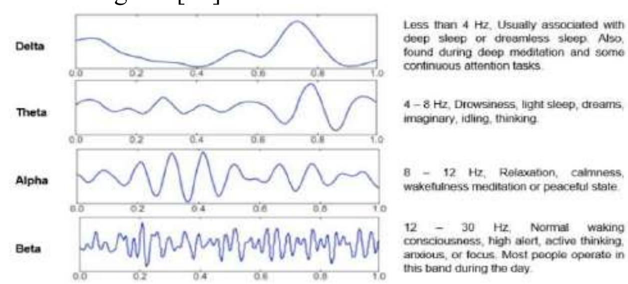


Fig. 1 Brainwave Signal
Source: Detecting Excessive Daytime Sleepiness with CNN and Commercial Grade EEG [15]

Based on Figure 1 above, each frequency of the resulting signal has a different meaning, so it is essential to classify the resulting frequency so that no wrong conclusions can be drawn to determine a person's condition, whether focused, asleep, relaxed and normal.

## III. Method

### A. Research Design

In this study, the author focuses on measuring students' attention levels when learning online using different devices. To measure the attention level of students, in this study, students were attached to a brain wave measuring device to record the frequencies produced when participating in online learning. At the final stage, this research is expected to be able to produce a conclusion that states the differences in the focus of students based on the devices used and can be input for educational institutions to recommend devices that are suitable for use in online learning because essentially online learning requires students to always be online screen time while following the lesson. The following is a research flow design that was carried out to find gaps among users of online learning tools. In this study, the authors used recorded data from students brain waves who were doing online learning using different devices, in this case used, smartphones and laptops. The number of students brain waves used for experimentation data is 25 students brain recording data. Each student will be given 15 minutes of learning material, and students will be allowed to focus on following the learning through a smartphone and then switch to using a laptop, but even though the learning is carried out for 15 minutes, the recorded brain wave data is only 5 minutes. This 5 minute recording minimizes abnormal data at the beginning and the end of the lesson. In this study, the age limit of students used as the research object is 18 - 22 years.

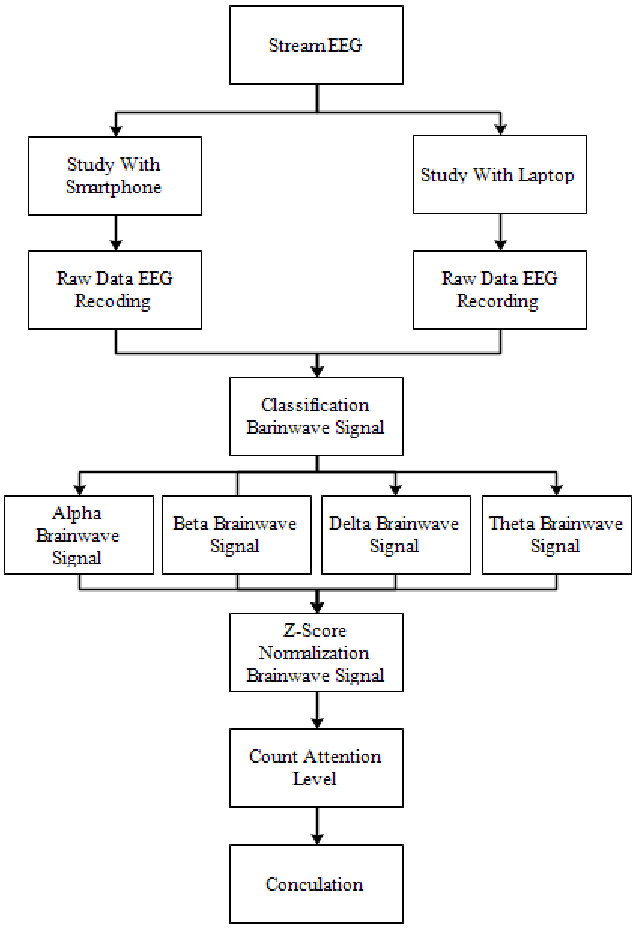

Fig. 2 Research Method

## B. EEG Signal Classification

The device used to record brain waves is Electroencephalography (EEG) globally, this device will record all brain waves using sensors located on the front and side of the device used. The results of the raw data recording of the brain waves will later be classified into a delta, theta, alpha, and beta signals.

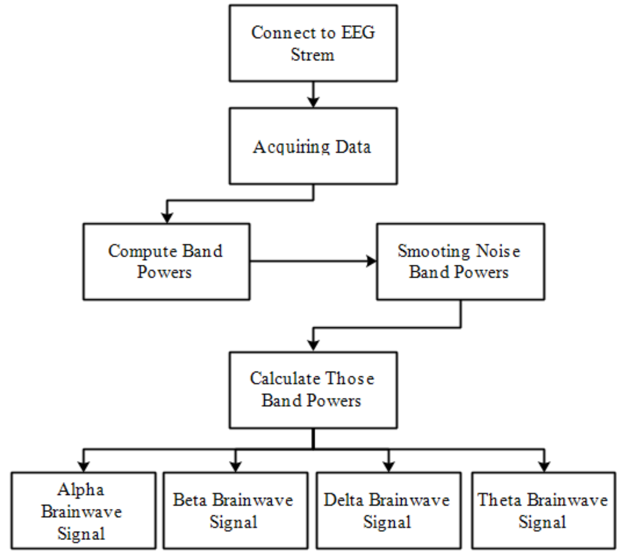

Fig. 3 EEG Signal Classification Process

This classification process begins by collecting all raw data identified from the tool, and then the data will be entered into the delta theta, alpha, and beta band signals. This classification process uses a formula provided by neurofeedback, where each time, the classification will generate a unique signal and later, the signal can be formulated into attention or relaxation. To measure the level of attention in the study using the formulation provided by MUSE neurofeedback, where the calculation used in the calculation of the machine is to take the beta_metric value taken by comparing smooth_band_powers [Band.Beta] and smooth_band_powers [Band.Theta].

## C. Preprocessing Signal EEG

One of the critical parts of this research is the retrieval of brain wave data which undergoes two stages before the data is finally ready to be entered into a classifier-based system. Before being processed in the classifier, the data will be normalized using the z-score normalization method with the following equation [16].

$$Z = \frac{X - \bar{X}}{SD_X} \tag{1}$$

After experiencing the first normalization stage, the brain waves will be processed again to get a sigma magnitude index which is helpful for detecting data outliers so that the classifier that will be made avoids local optimum or overfitting problems. The amortization formula to be used in this study is as follows [17].

$$\mathrm{SMA} = \sum_{i=1}^{N-1} | x_{(i+1)} - x_i | \tag{2}$$

The normalized data must first have a threshold so that there is no noise during processing. The determination of the threshold or threshold in this study uses the following equation.

$$EEGThreshold_{(x)} = AVG(SMAs_{(x)}) + STD(SMAs_{(x)}) \quad (3)$$

The process carried out in the above formula is to determine the threshold according to the context of the data carried out where it is expected from the results of these calculations to form brain wave data with the threshold used as a natural evaluator as a comparison of individuals to the population.

### D. Testing Scenario

The test scenario of this option begins with recording data using an EEG device, and then the results of the raw data recording will be classified so as to produce alpha, theta, beta and delta signals. The classified brain wave signals will then enter the preprocessing process using the z-score normalization formula. The purpose of normalizing the z-score is to facilitate the processing process that can truly distinguish each signal needed to determine the attention level of students. After all the signals are recorded correctly, a formulation will be carried out to determine the level of students' attention by comparing the beta signal, which should be greater than theta, so it can be said that the student has concentration. As for the number of users used in this experiment, there were 25 students. The student will be given the task of completing online learning using two different supporting devices, namely smartphones and laptops.

Fig. 4 Testing Using Smartphone

Fig. 5 Testing Using a Laptop

In this test scenario, students will be asked to take part in online learning by answering questions that have been provided using a smartphone application and an application on a laptop for 15 minutes. Although online learning is carried out for 15 minutes, the researcher will not record the first 5 minutes using the EEG tool because, in the first 5 minutes, the researcher assumes that students are adapting to the given task so that the brain wave data recorded in this study is 10 minutes in the learning session online. The results of each user's brain wave recordings will be compared when using laptops and smartphones so that later results will be obtained in the form of how big the difference in effectiveness is in maintaining the attention level of students when participating in online learning.

## IV. Result and Discussion

### A. Brainwave Classification Results

The following are the results of the classification of brain waves generated by implementing a formula in the python programming language so that the system can break down raw data into four signals that are needed to measure students attention levels.

TABLE I
SAMPLE OF BRAIN WAVE SIGNAL CLASSIFICATION RESULT

| User | EEG Signal Result | | | |
|---|---|---|---|---|
| | Alpha | Theta | Beta | Delta |
| 1 | 0.12 | 0.55 | 0.77 | 0.73 |
| 2 | 0.74 | 0.58 | 0.22 | 0.98 |
| 3 | 0.38 | 0.59 | 0.89 | 0.28 |
| 4 | 0.23 | 0.65 | 0.50 | 0.15 |
| 5 | 0.52 | 0.50 | 0.24 | 0.05 |
| 6 | 0.02 | 0.33 | 0.65 | 0.93 |
| 7 | 0.30 | 0.22 | 0.94 | 0.78 |
| 8 | 0.01 | 0.68 | 0.25 | 0.10 |
| 9 | 0.41 | 0.05 | 0.36 | 0.85 |
| 10 | 0.25 | 0.99 | 0.29 | 0.43 |
| 11 | 0.07 | 0.02 | 0.25 | 0.58 |
| 12 | 0.06 | 0.28 | 0.21 | 0.49 |
| 13 | 0.42 | 0.99 | 0.80 | 0.53 |
| 14 | 0.84 | 0.21 | 0.37 | 0.93 |
| 15 | 0.61 | 0.26 | 0.63 | 0.29 |
| 16 | 0.57 | 0.07 | 0.42 | 0.51 |
| 17 | 0.77 | 0.78 | 0.81 | 0.99 |
| 18 | 0.30 | 0.52 | 0.56 | 0.30 |
| 19 | 0.16 | 0.78 | 0.94 | 0.93 |
| 20 | 1.00 | 0.39 | 0.11 | 0.75 |
| 21 | 0.73 | 0.61 | 0.20 | 0.10 |
| 22 | 0.96 | 0.83 | 0.48 | 0.15 |
| 23 | 0.44 | 0.39 | 0.86 | 0.54 |
| 24 | 0.91 | 0.75 | 0.58 | 0.57 |
| 25 | 0.17 | 0.31 | 0.25 | 0.92 |

Table 1 is an example of brain wave recordings that have been carried out in this study, which in this study specifically took alpha, theta, beta and delta signals because by getting these signals, researchers could analyze students attention levels.

TABLE II
AVERAGE OF BRAIN WAVE SIGNAL CLASSIFICATION RESULT

| EEG Signal | Average Signal Result | Number of User |
|---|---|---|
| Alpha | 0.55 | 25 |
| Theta | 0.46 | 25 |
| Beta | 0.58 | 25 |
| Delta | 0.41 | 25 |

Based on the results of data recording 25 students, table 2 shows the average results of recording the four types of brain wave data, where beta and alpha signals have the highest average value when someone still online learning.

### B. *Test Results on Smartphones and Laptops*

The following is the result of calculating the attention level of students when using two different devices where the results of this attention level are obtained from recording for ten minutes, and the results shown in the following table are the average values of the 10 minutes recording.

TABLE III
SAMPLE OF ATTENTION LEVEL TEST RESULT

| User | Attention Level | |
|---|---|---|
| | Use Laptop (%) | Use Smartphone (%) |
| 1 | 63 | 61 |
| 2 | 60 | 50 |
| 3 | 56 | 45 |
| 4 | 65 | 51 |
| 5 | 58 | 42 |
| 6 | 57 | 52 |
| 7 | 61 | 54 |
| 8 | 51 | 54 |
| 9 | 70 | 62 |
| 10 | 59 | 54 |
| 11 | 67 | 60 |
| 12 | 64 | 61 |
| 13 | 65 | 60 |
| 14 | 67 | 65 |
| 15 | 62 | 56 |
| 16 | 52 | 60 |
| 17 | 59 | 40 |
| 18 | 68 | 68 |
| 19 | 60 | 58 |
| 20 | 60 | 52 |
| 21 | 63 | 53 |
| 22 | 70 | 50 |
| 23 | 63 | 50 |
| 24 | 50 | 45 |
| 25 | 50 | 65 |

Table 3 is the result of the attention level of 25 students when using two different devices in this research use laptops and smartphones. If you see at a glance, there are slight differences in attention levels when using laptops and smartphones, and to see the differences in depth, it can be analyzed by looking at the average of all number of study members.

TABLE IV
AVERAGE OF ATTENTION LEVEL TEST RESULT

| No | Device | Average Attention Level (%) | Number of User |
|---|---|---|---|
| 1 | Laptop | 60.80 | 25 |
| 2 | Smartphone | 54,72 | 25 |

Based on table 4, it can be seen that the students attention level value when using a laptop has a higher value than using a smartphone. Based on the data presented in table 4, the attention level when learning to use a laptop has a higher value of 5.76% compared to a smartphone device.

### C. *Analysis Results*

Based on the tests that have been carried out, the developed system has been able to classify raw brain wave data into signals or frequencies needed for formulating attention level calculations.

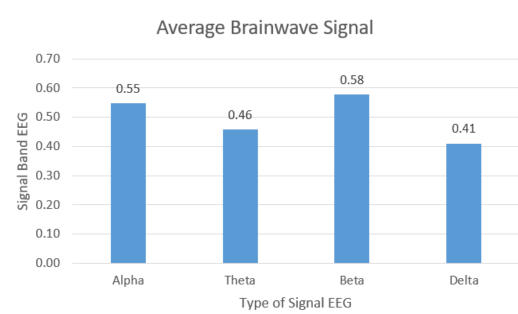


Fig. 6 EEG Signal Classification Graph

In addition to classifying the developed system, it has also been able to normalize brain wave signals using the z-score formulation, where the normalization results will undoubtedly make it easier for researchers to filter out which signals are used for calculating the extension level. The following is a graph of what happens when students do online learning using smartphones and laptops.

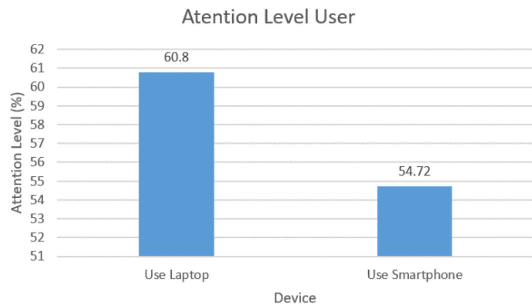


Fig. 7 Graph of Learning Device Comparison Results

Based on the graph that has been presented, it can be seen that there is not a big gap when online learning is carried out using a smartphone or laptop, but if taken on average, online learning using a laptop has a higher attention level value than using a smartphone, although not too much significant. This insignificant result may be generated because the activity is only carried out for 15 minutes. Of course, it will produce different values when analyzing brain wave data with a longer duration in the future. In general, the author can conclude that using a laptop will be more effective in maintaining the attention level of students in participating in online lessons based on level test results generated from students' brain waves.

## V. CONCLUSION

The conclusion obtained from this study is that the use of the classification method provided by neurofeedback is able to divide the raw data into a delta, theta, alpha, and beta signals. Based on the results of tests carried out using two different devices, it can be concluded that there is no gap that is too high when students use laptops or smartphones in participating in online learning, which is carried out for a duration of 15 minutes but in general, the attention level value when using a laptop has a high value higher than using a smartphone, which has a difference of 5.76% where the attention level of students will be higher when using a laptop device, 60.80% for laptops and 54.72% for smartphones conducted by observing students with an age range of 18-22 years. In its application, the tools used in this study are still focused on brain wave recording devices, in the future the sensors on this device can be implanted in the headset so that the tools used can also have other functions other than only being used to record brain waves and may look quite disturbing if only has one function.

## ACKNOWLEDGMENT

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# Effect of Different Online Learning Screen Sizes During the COVID-19 Pandemic: An EEG Study

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***Abstract*—The COVID-19 pandemic has given rise to a different learning paradigm than before, from offline learning to online learning. This paradigm is, of course, still popularly used today even until the pandemic ends in the future. The learning paradigm in question is the online learning method. Online learning method not only provides convenience for students or educators but also creates problems that are very interesting to observe. One of the variables that become a problem in this learning method is the students' level of focus in online learning because online learning requires a lengthy screen time, and students use different devices. In this study, we will analyze the level of focus of students participating in online learning using smartphones and laptops. The problem with online learning is the different focus conditions due to differences in the use of devices, affecting the delivery of material received by students. The age limit of students used as the research object is 18-20 years. The approach used to analyze this problem is measure the level of focus using a brain wave recorder Electroencephalogram (EEG). As many as 25 students will observe their level of focus when participating in online learning using laptops and smartphones. Based on research conducted, the focus level of students using smartphone devices has an attention level of 54.72% and laptops by 60.80%. Laptop use has a higher level of attention by 5.76% than smartphone use.**

Keywords—Student Focus, Attention Level, Post Pandemic Education, Elektroensefalogram (EEG), Brainwave.

## I. Introduction

The COVID-19 pandemic from the end of 2019 until now has not ended, new variants of this virus keep popping up, which causes people to have to get used to the new habits that are present today both in the education sector, work, and other sectors. During the early days of the pandemic, all teaching and learning processes were abolished to limit the spread of this virus, and after a while the idea emerged to organize online education. This idea is stated in the decree of the Minister of Education Number 4 of 2020 which requires online learning for Indonesian higher education [1]. To overcome the paradigm during the pandemic, schools use online learning methods to make students still able to study comfortably without fear of being exposed to the COVID-19 virus. This online learning method is certainly many questions for academics, both in terms of the seriousness of students, interactions and the effectiveness of this learning method. Although research on the effectiveness of distance learning via the internet has been widely carried out [2], not much has been done on a large scale like this [3], not only in terms of education but also because many previous studies have been conducted in the health sector, especially in the field of eye and eye health ergonomics [4]. The variety of tools used in online learning is a very interesting research topic to observe, judging from previous research that took the case of students' eye health and ergonomics in the implementation of online learning, in this study, observations will be made regarding how students concentrate when doing online learning using tools, the most frequently used are smartphones and laptops based on brain wave observations using an electroencephalogram (EEG). Research that compares the effectiveness of screen sizes in online learning has been conducted but has not touched the realm of analysis using EEG, where the research topic is still in the realm of learning methods and to get the results of effectiveness analysis using different screen sizes, test results are used. [5], [6].

The electroencephalogram itself is a device used to record electrical activity in the brain, where by using standard sensors found on the EEG device, researchers can record several waves such as Alpha, Beta, Delta and Theta. Each brain wave produced will be calculated to be able to draw conclusions about how much concentration of students is when carrying out online learning using different devices. The importance of this research is because, in its application, online learning requires students to always be on screen time during the learning process, where the length of the learning process cannot be said to run in a short time. The average learning process carried out for each session in a university

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environment is 45 minutes. The question that arises from the example case is whether students are still focused on receiving online learning at that time.

Previous case studies between human and computer interactions observed based on brain waves have actually been carried out, and these brain waves have become a commonly used parameter to detect the dynamics of interactions that occur [7], although on several occasions, it has been proven that brain wave parameters tend to be more stable and stable. Of its reliability or can be said to be more tested than other biological parameters. Brain waves are a test parameter that is often used in defence-based research [8], research in the advertising branch of science and research in psychology and psychology. In the early stages of this research, the students will record brain wave signals while learning using smartphones and laptops. The brain wave signals obtained in the early stages will be in the form of band powers. Later, the power bands will be classified based on Alpha, Beta, Delta and Theta signals. After successfully classified, the signal will be normalized and processed to produce the attention value of each student when using smartphones and laptops so that later it will be able to compare how the students' attention differs when carrying out online learning using the two devices. The contribution that the author can give to the next research is that it is hoped that with this research in the future, the education provider can provide input to students or parents of students to recommend learning devices, especially in terms of the type of screen that is suitable for use to support the learning process so that even though learning is carried out online, the focus of students in transfer knowledge given can be maximized.

## II. Related Work

### A. *Related Research*

Research related to the effectiveness of distance learning via the internet has been done a lot [2]. However, when compared to a large scale, this research model has not been widely carried out [3] because this online learning paradigm only jumped when the COVID-19 pandemic hit the world since 2019 ago. Until now, research related to student learning concentration has not been widely studied using brain wave condition parameters, previous studies have mostly taken cases in the form of qualitative studies from the side of students [2]. In this study, the authors tried to analyze the focus of students' learning by observing brain waves using Electroencephalography (EEG) devices. Many studies using EEG have actually been carried out, but only a few have touched on the world of education, research related to EEG has mostly touched on the realm of fatigue [4], and the most frequent causes of fatigue raised using EEG analysis are cases of transportation fatigue [9], [10], [11], [12]. Based on the lack of focus on student learning cases who were appointed by conducting brain wave analysis, in this study, the researchers wanted to see the effectiveness of the implementation of online learning using the most frequently used tools for online learning.

### B. *Electroencephalography*

The tool that can be used to read a person's brain waves is an Electroencephalography (EEG) device [13], research using EEG actually became popular in the era after the second world war when it began to find indications that the human brain emits small electrical impulses which can eventually be captured and transmitted read to indicate certain biological symptoms as well as biological activities such as muscle movement and eye movement [14]. The domain that is often detected using EEG is fatigue detection in transportation research, where EEG as a device is used to read human brain waves, study them and draw certain conclusions, as well as make safety devices. In addition to the transportation field, brain wave readings can also be used to see the amount of meditation and concentration level for each user, where the level is by formulating the main signal that the brain wave reader can record. The standard signals that can be extracted from the raw brain wave data produced are Alpha, Beta, Delta and Theta signals [15].

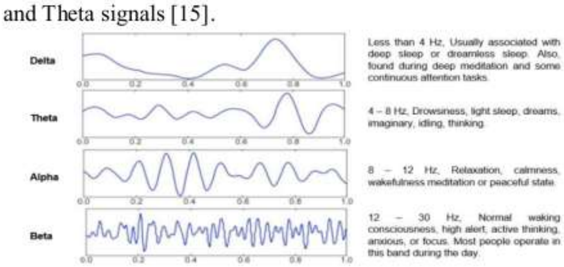


Fig. 1 Brainwave Signal
Source: Detecting Excessive Daytime Sleepiness with CNN and Commercial Grade EEG [15]

Based on Figure 1 above, each frequency of the resulting signal has a different meaning, so it is essential to classify the resulting frequency so that no wrong conclusions can be drawn to determine a person's condition, whether focused, asleep, relaxed and normal.

## III. Method

### A. *Research Design*

In this study, the author focuses on measuring students' attention levels when learning online using different devices. To measure the attention level of students, in this study, students were attached to a brain wave measuring device to record the frequencies produced when participating in online learning. At the final stage, this research is expected to be able to produce a conclusion that states the differences in the focus of students based on the devices used and can be input for educational institutions to recommend devices that are suitable for use in online learning because essentially online learning requires students to always be online screen time while following the lesson. The following is a research flow design that was carried out to find gaps among users of online learning tools. In this study, the authors used recorded data from students brain waves who were doing online learning using different devices, in this case used, smartphones and laptops. The number of students brain waves used for experimentation data is 25 students brain recording data. Each

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student will be given 15 minutes of learning material, and students will be allowed to focus on following the learning through a smartphone and then switch to using a laptop, but even though the learning is carried out for 15 minutes, the recorded brain wave data is only 5 minutes. This 5 minute recording minimizes abnormal data at the beginning and the end of the lesson. In this study, the age limit of students used as the research object is 18 - 22 years.

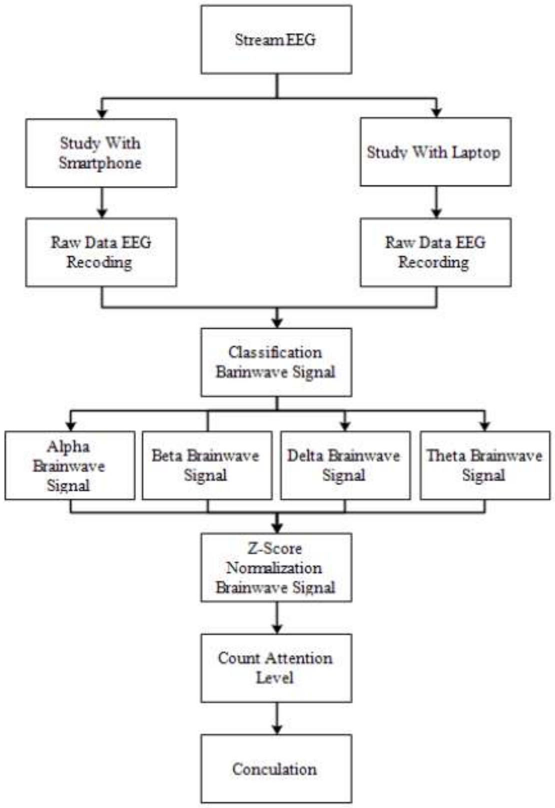


Fig. 2 Research Method

### B. EEG Signal Classification

The device used to record brain waves is Electroencephalography (EEG) globally, this device will record all brain waves using sensors located on the front and side of the device used. The results of the raw data recording of the brain waves will later be classified into a delta, theta, alpha, and beta signals.

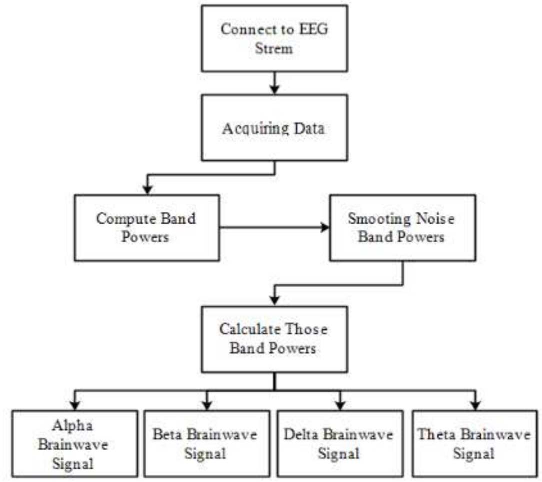


Fig. 3 EEG Signal Classification Process

This classification process begins by collecting all raw data identified from the tool, and then the data will be entered into the delta theta, alpha, and beta band signals. This classification process uses a formula provided by neurofeedback, where each time, the classification will generate a unique signal and later, the signal can be formulated into attention or relaxation. To measure the level of attention in the study using the formulation provided by MUSE neurofeedback, where the calculation used in the calculation of the machine is to take the beta_metric value taken by comparing smooth_band_powers [Band.Beta] and smooth_band_powers [Band.Theta].

### C. Preprocessing Signal EEG

One of the critical parts of this research is the retrieval of brain wave data which undergoes two stages before the data is finally ready to be entered into a classifier-based system. Before being processed in the classifier, the data will be normalized using the z-score normalization method with the following equation [16].

$$Z = \frac{X - \bar{X}}{SD_x} \tag{1}$$

After experiencing the first normalization stage, the brain waves will be processed again to get a sigma magnitude index which is helpful for detecting data outliers so that the classifier that will be made avoids local optimum or overfitting problems. The amortization formula to be used in this study is as follows [17].

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

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The normalized data must first have a threshold so that there is no noise during processing. The determination of the threshold or threshold in this study uses the following equation.

$$EEGThreshold_{(x)} = AVG(SMAs_{(x)}) + STD(SMAs_{(x)}) \quad (3)$$

The process carried out in the above formula is to determine the threshold according to the context of the data carried out where it is expected from the results of these calculations to form brain wave data with the threshold used as a natural evaluator as a comparison of individuals to the population.

### D. Testing Scenario

The test scenario of this option begins with recording data using an EEG device, and then the results of the raw data recording will be classified so as to produce alpha, theta, beta and delta signals. The classified brain wave signals will then enter the preprocessing process using the z-score normalization formula. The purpose of normalizing the z-score is to facilitate the processing process that can truly distinguish each signal needed to determine the attention level of students. After all the signals are recorded correctly, a formulation will be carried out to determine the level of students' attention by comparing the beta signal, which should be greater than theta, so it can be said that the student has concentration. As for the number of users used in this experiment, there were 25 students. The student will be given the task of completing online learning using two different supporting devices, namely smartphones and laptops.

Fig. 4 Testing Using Smartphone

Fig. 5 Testing Using a Laptop

In this test scenario, students will be asked to take part in online learning by answering questions that have been provided using a smartphone application and an application on a laptop for 15 minutes. Although online learning is carried out for 15 minutes, the researcher will not record the first 5 minutes using the EEG tool because, in the first 5 minutes, the researcher assumes that students are adapting to the given task so that the brain wave data recorded in this study is 10 minutes in the learning session online. The results of each user's brain wave recordings will be compared when using laptops and smartphones so that later results will be obtained in the form of how big the difference in effectiveness is in maintaining the attention level of students when participating in online learning.

## IV. Result and Discussion

### A. Brainwave Classification Results

The following are the results of the classification of brain waves generated by implementing a formula in the python programming language so that the system can break down raw data into four signals that are needed to measure students attention levels.

TABLE I
SAMPLE OF BRAIN WAVE SIGNAL CLASSIFICATION RESULT

| User | EEG Signal Result | | | |
|---|---|---|---|---|
| | Alpha | Theta | Beta | Delta |
| 1 | 0.12 | 0.55 | 0.77 | 0.73 |
| 2 | 0.74 | 0.58 | 0.22 | 0.98 |
| 3 | 0.38 | 0.59 | 0.89 | 0.28 |
| 4 | 0.23 | 0.65 | 0.50 | 0.15 |
| 5 | 0.52 | 0.50 | 0.24 | 0.05 |
| 6 | 0.02 | 0.33 | 0.65 | 0.93 |
| 7 | 0.30 | 0.22 | 0.94 | 0.78 |
| 8 | 0.01 | 0.68 | 0.25 | 0.10 |
| 9 | 0.41 | 0.05 | 0.36 | 0.85 |
| 10 | 0.25 | 0.99 | 0.29 | 0.43 |
| 11 | 0.07 | 0.02 | 0.25 | 0.58 |
| 12 | 0.06 | 0.28 | 0.21 | 0.49 |
| 13 | 0.42 | 0.99 | 0.80 | 0.53 |
| 14 | 0.84 | 0.21 | 0.37 | 0.93 |
| 15 | 0.61 | 0.26 | 0.63 | 0.29 |
| 16 | 0.57 | 0.07 | 0.42 | 0.51 |
| 17 | 0.77 | 0.78 | 0.81 | 0.99 |
| 18 | 0.30 | 0.52 | 0.56 | 0.30 |
| 19 | 0.16 | 0.78 | 0.94 | 0.93 |
| 20 | 1.00 | 0.39 | 0.11 | 0.75 |
| 21 | 0.73 | 0.61 | 0.20 | 0.10 |
| 22 | 0.96 | 0.83 | 0.48 | 0.15 |
| 23 | 0.44 | 0.39 | 0.86 | 0.54 |
| 24 | 0.91 | 0.75 | 0.58 | 0.57 |
| 25 | 0.17 | 0.31 | 0.25 | 0.92 |

Table 1 is an example of brain wave recordings that have been carried out in this study, which in this study specifically took alpha, theta, beta and delta signals because by getting these signals, researchers could analyze students attention levels.

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TABLE II

AVERAGE OF BRAIN WAVE SIGNAL CLASSIFICATION RESULT

| EEG Signal | Average Signal Result | Number of User |
|---|---|---|
| Alpha | 0.55 | 25 |
| Theta | 0.46 | 25 |
| Beta | 0.58 | 25 |
| Delta | 0.41 | 25 |

Based on the results of data recording 25 students, table 2 shows the average results of recording the four types of brain wave data, where beta and alpha signals have the highest average value when someone still online learning.

### B. *Test Results on Smartphones and Laptops*

The following is the result of calculating the attention level of students when using two different devices where the results of this attention level are obtained from recording for ten minutes, and the results shown in the following table are the average values of the 10 minutes recording.

TABLE III

SAMPLE OF ATTENTION LEVEL TEST RESULT

| User | Attention Level | |
|---|---|---|
| | Use Laptop (%) | Use Smartphone (%) |
| 1 | 63 | 61 |
| 2 | 60 | 50 |
| 3 | 56 | 45 |
| 4 | 65 | 51 |
| 5 | 58 | 42 |
| 6 | 57 | 52 |
| 7 | 61 | 54 |
| 8 | 51 | 54 |
| 9 | 70 | 62 |
| 10 | 59 | 54 |
| 11 | 67 | 60 |
| 12 | 64 | 61 |
| 13 | 65 | 60 |
| 14 | 67 | 65 |
| 15 | 62 | 56 |
| 16 | 52 | 60 |
| 17 | 59 | 40 |
| 18 | 68 | 68 |
| 19 | 60 | 58 |
| 20 | 60 | 52 |
| 21 | 63 | 53 |
| 22 | 70 | 50 |
| 23 | 63 | 50 |
| 24 | 50 | 45 |
| 25 | 50 | 65 |

Table 3 is the result of the attention level of 25 students when using two different devices in this research use laptops and smartphones. If you see at a glance, there are slight differences in attention levels when using laptops and smartphones, and to see the differences in depth, it can be analyzed by looking at the average of all number of study members.

TABLE IV

AVERAGE OF ATTENTION LEVEL TEST RESULT

| No | Device | Average Attention Level (%) | Number of User |
|---|---|---|---|
| 1 | Laptop | 60.80 | 25 |
| 2 | Smartphone | 54,72 | 25 |

Based on table 4, it can be seen that the students attention level value when using a laptop has a higher value than using a smartphone. Based on the data presented in table 4, the attention level when learning to use a laptop has a higher value of 5.76% compared to a smartphone device.

### C. *Analysis Results*

Based on the tests that have been carried out, the developed system has been able to classify raw brain wave data into signals or frequencies needed for formulating attention level calculations.

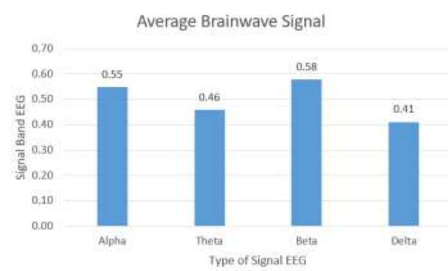


Fig. 6 EEG Signal Classification Graph

In addition to classifying the developed system, it has also been able to normalize brain wave signals using the z-score formulation, where the normalization results will undoubtedly make it easier for researchers to filter out which signals are used for calculating the extension level. The following is a graph of what happens when students do online learning using smartphones and laptops.

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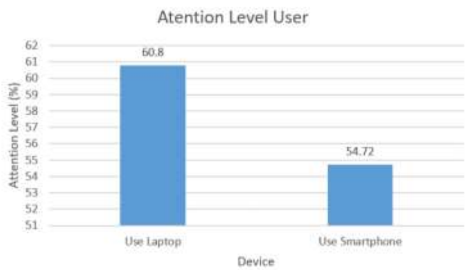


Fig. 7 Graph of Learning Device Comparison Results

Based on the graph that has been presented, it can be seen that there is not a big gap when online learning is carried out using a smartphone or laptop, but if taken on average, online learning using a laptop has a higher attention level value than using a smartphone, although not too much significant. This insignificant result may be generated because the activity is only carried out for 15 minutes. Of course, it will produce different values when analyzing brain wave data with a longer duration in the future. In general, the author can conclude that using a laptop will be more effective in maintaining the attention level of students in participating in online lessons based on level test results generated from students' brain waves.

## V. Conclusion

The conclusion obtained from this study is that the use of the classification method provided by neurofeedback is able to divide the raw data into a delta, theta, alpha, and beta signals. Based on the results of tests carried out using two different devices, it can be concluded that there is no gap that is too high when students use laptops or smartphones in participating in online learning, which is carried out for a duration of 15 minutes but in general, the attention level value when using a laptop has a high value higher than using a smartphone, which has a difference of 5.76% where the attention level of students will be higher when using a laptop device, 60.80% for laptops and 54.72% for smartphones conducted by observing students with an age range of 18-22 years. In its application, the tools used in this study are still focused on brain wave recording devices, in the future the sensors on this device can be implanted in the headset so that the tools used can also have other functions other than only being used to record brain waves and may look quite disturbing if only has one function.

## Acknowledgment

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