K-Nearest Neighbor of Beta Signal Brainwave to Accelerate Detection of Concentration on Student Learning Outcomes

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Abstract—**Intelligence, creativity, emotions, memory, and body movements are human activities controlled by the brain. While humans do an activity, the neural network in the brain produces an electrical current in the form of waves. Brainwaves are one of the biometric features that can be used to identify individual characteristics based on their activity and behavior patterns. Identifying individual characteristics requires a brain activity measurement using an Electroencephalogram (EEG). Measuring brainwaves requires a reliable, prominent, and constant activity stimulation by applying a series of cognitive tasks, such as the Culture Fair Intelligence Test (CFIT) and the Indonesian Competency Test (CT). This research aims to obtain relation patterns and accelerate the detection between brain concentration and learning outcomes. Beta signal acquisition is obtained from junior high school students while performing cognitive tasks. After data is obtained, the signal is extracted using the Fast Fourier Transform (FFT) to get its peak signal. The peak signal from FFT data on CFIT generated an average score of 0.214 with the category of *Average*. Meanwhile, the peak signal on CT generated an average score of 0.246 with the category "C+". K-Nearest Neighbor (KNN) algorithm is applied to identify patterns from extraction data with K-value=5; then, the accuracy is assessed using K-Fold Cross Validation with K-value=11. The resulting accuracy is 94.59%. Based on the KNN classification results, students' learning outcomes are influenced by their concentration. This research has successfully shortened the CFIT evaluation time from three days to one day.**

Index Terms— **Brainwaves, Electroencephalogram, Cognitive Task, Fast Fourier Transform, K-Nearest Neighbor**

I. Introduction

Technology has been developed to help society in various fields, such as in education [1]–[3], business [4], culture [5], and health [6]–[9]. Many healthcare technologies have been developed, one of which is to help the process of identifying diseases suffered by patients with the help of medical devices such as Electroencephalogram (EEG) [6] and Electrocardiogram (ECG) [10]. EEG scans help doctors make decisions while diagnosing a patient's illness. EEG measures electrical patterns on the surface of the scalp that reflects cortical activity, commonly called brain waves.

Study finding [7] revealed that the brain could record its electric current (in waves) at low currents without opening the skull and wrapping it on paper. EEG is developed and is rapidly used in many fields, especially in neurology, physiology, and psychology. In general, there are two types of EEG devices, namely the scalp EEG (mounted outside of the patient's head) and the intracranial EEG (mounted above the brain membrane, usually through a surgical process). Intracranial EEG (IEEG) is usually limitedly used in some instances, e.g., before surgery, to diagnose or map more parts of brain abnormalities.

EEG connection with a computer or other devices can be wired or wireless [11]. EEG has very diverse applications. They can be applied in the healthcare systems, such as Brain-Computer Interface (BCI) and robotics [12]. To this date, the most critical EEG application is in the healthcare systems. EEG is generally used in healthcare and medical systems to diagnose, monitor, and analyze brain disorders or how the brain works [12][13]. EEG is very commonly used to diagnose epilepsy [6]. EEG is also used to detect and analyze sleep disorders that indicate brain damage. EEG is also potential to be studied or conducted in therapy for children with Autism, Attention Deficit Hyperactivity Disorder (ADHD), or children who experience learning disabilities (Learning Disorder) [15].

Learning disorders are neurological disorders that affect concentration while receiving, processing, analyzing, or storing information [16]. Concentration has a major impact on children's learning process; it can be a causal factor of learning disorders. Children with learning disorders or low concentrations may have the same or even higher intelligence levels compared to their peers but often struggle to learn as fast as those around them. Some problems related to mental health and learning disorders are difficulties in reading, writing, spelling, remembering, reasoning, as well as motor skills, and problem-solving skills in mathematics. According to the National Joint Committee for Learning Disabilities (NJCLD), learning disorders are groups with various disorders that cause difficulties in listening, speaking, writing, analyzing, and solving problems [17]. Learning disabilities can cause depression because it is challenging to understand problems and find solutions. Children with learning disabilities cannot produce achievements from learning outcomes. However, it does not necessarily mean that children with learning disorders have a low level of intelligence.

Based on the explanation above, the amount of time needed by a child to understand a problem indicates whether the child has learning difficulties or not. A psychological assessment

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test, called the Culture Fair Intelligence Test (CFIT), can be carried out to determine how much the child's brain can overcome learning difficulties. This study tries to obtain a pattern of concentration in learning outcomes using the EEG Neurosky Mindwave Mobile 2 device, which will be mounted on the surface of the head without performing surgical operations so that it is possible to speed up the process of recording EEG signals.

II. Methods

Section 2 will discuss the theoretical basis and methods used in this research.

A. Block Diagram of Proposed Method

This study has four research stages: data acquisition, FFT, classification, and evaluation. This research will use Neurosky Mindwave Mobile 2 as a signal data acquisition tool. Then, MATLAB will be used to perform FFT. After getting the features from FFT, the classification process will be carried out using KNN in Python. After the classification process is complete, the evaluation process will be carried out with K-Fold Cross Validation to determine the system's accuracy. The block diagram of the proposed research method can be seen in Fig. 1.

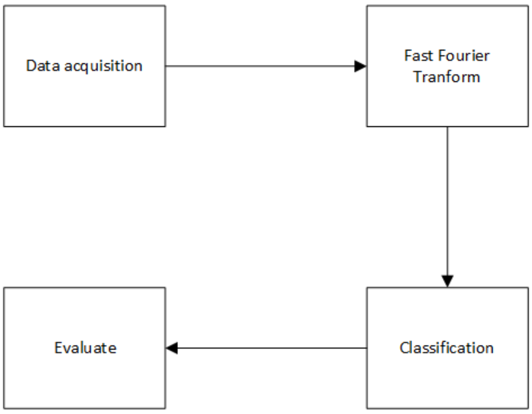


Fig. 1. Proposed Research Method

B. Brainwave Oscillations

Brainwave is measured in two ways: measurement of amplitude and frequency. Amplitude is the magnitude of the power impulse measured in microvolt (µV) units. Frequency is the speed of power emissions measured in cycles per second or Hertz (Hz). The frequency of impulses determines the type of brain waves produced [18]. Waves generated by the brain during the activity can be divided into five EEG signal patterns: Alpha, Beta, Theta, Delta, and Gamma. Table 1 shows the list of neural oscillations [19], including their respective types, brain conditions, and frequencies.

Transmission activity during the EEG process will affect the pattern of brainwaves formation. In this study, concentration is the main focus of data collection. Concentration falls into the beta signal category because beta waves aim to help humans maintain focus when engaging in activities that require concentration [19]. The potential for electricity produced by the brain is less than 300 µV. Previous study findings [20] suggested that the magnitude of EEG signal is in the range of 50 to 100 µV.

TABLE I
OSCILLATIONS OF BRAINWAVE

Wave Type	Frequency Range	Mental States
Delta	0.5 - 4 Hz	*Deep sleep* conditions without dreaming. Body rest phase.
Theta	4 - 8 Hz	Meditation, intimacy, and fantasy conditions.
Alpha	8 - 15 Hz	Conditions of relaxation and wakefulness.
Beta	15 - 32 Hz	Conditions of focus, thinking, and concentration (external attention). Body productivity phase.
Gamma	32 - 50 Hz	High mental activities such as fear, panic, and high concentration.

C. K-Nearest Neighbor

K-Nearest Neighbor is an algorithm used to classify data. The obtained data must be processed with distance measurements using Euclidean Distance to find the nearest neighbor [21][22]. The K values used in KNN are random and integer. The visualization of KNN can be seen in Fig. 2.

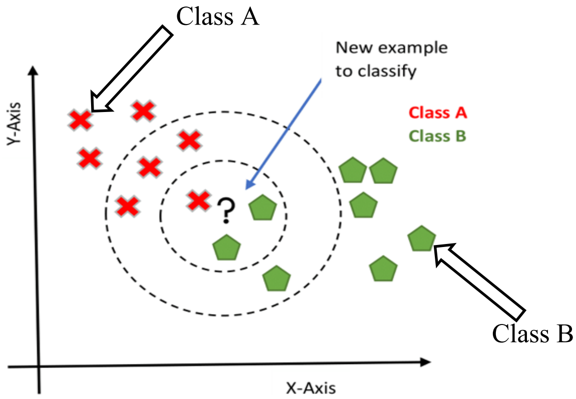


Fig. 2. KNN Visualization

If two data are already known (classified), then the class of data X can be determined by looking at the nearest K. For example, when the K = 3 (inside the smallest circle), it can be known that the class of three-nearest neighbors of X are red, green, green. Because 80% of the nearest neighbors are classified as green, the class prediction of data X is green. Whereas, if K = 7 (inside the bigger circle), then the class of the seven-closest neighbors of data X is red, red, red, red, green, green, green. So, the predicted class of data X is red. In other words, the KNN algorithm is an algorithm for classification based on the most dominant class based on the specified value of K.

Pseudo-Code for KNN:

- Training algorithm
    1. For each classless training data, add the example to the list of *Training Dataset*.
- Classification algorithm
    1. Specify a value of K
    2. Calculate the distance using the Euclidean distance formula
    3. Sort the distance based on the closest distance
    4. Specify the closest distance according to the K number

The first step in applying KNN is determining the K value that will be the number of neighbors for later calculation results. After determining the K value, the distance calculation will be done using equation (1). After calculating the distance, the next step will be to sort the data according to the closest distance based on the specified value of K. After that stage is completed, the last stage will display the classification results according to the K value.

$$d = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} \quad (1)$$

where x_1 and y_1 are the value of testing data (data with class) and x_2 and y_2 are the value of training data (new classless data).

D. Fast Fourier Transform

The feature extraction is used to get the pattern of the tested signal [23]. Feature extraction is the initial process to carry out the process of classification and interpretation of signals [24][25]. This extraction process is related to the characteristics of the corresponding signal values. One of the extraction methods is the Fast Fourier Transform. Fourier Transform (FFT) is a source of algorithms to calculate Discrete Fourier Transform (DFT) quickly, efficiently, and vice versa [16][17]. FFT has been applied in various fields of digital signal processing and solved large numbers of differential equations. The primary classes of the FFT algorithm are Decimation in Time (DIT) and Decimation in Frequency (DIF). The outline word is interpreted quickly because the FFT formulation is faster than the previous Fourier Transform calculation method. One form of transformation commonly used to convert signals from the time-domain to the frequency-domain is the Fourier transform [28].

FFT in signal processing is related to frequency and period [29]:

1. Frequency

   Frequency is the amount of pearlescence that occurs within one second or the number of waves/vibrations generated every second.

2. Period

   The period is the length of time it takes to perform one perfect wave vibration. The relationship between frequency and period is inversely proportional.

Pseudo-Code for FFT:

1. Add raw signal as input that will be changed into a spectrum signal
2. Get the maximum and minimum value of peak signal
3. Calculate the average of the maximum and minimum peak signal
4. Calculate the average of peak signal magnitudes

E. Data Acquisition

Data acquisition is the stage of data retrieval that will be used in research. The data used in this study are primary data. EEG tools are used to obtain brainwave data while respondents are given a stimulus, cognitive tasks [30]. Data acquisition in this study was carried out twice with a span of seven days on each iteration. In this process, data results were successfully obtained from 117 respondents. Respondents consisted of 58 males and 59 females aged 10-12 years old, from Muhammadiyah Junior High School 3 Yogyakarta, Indonesia. Respondents were willing to take CFIT and CT Indonesian tests and be paired with Mindwave Mobile 2 Neurosky as an EEG recording tool while answering the test. The recording duration with EEG is 15 minutes for the CFIT test and 10 minutes for the CT Indonesian test.

F. Culture Fair Intelligence Test

Culture Fair Intelligence Test is a tool developed by R. B. Cattel in 1973. CFIT measures individual intelligence in a planned manner to reduce the influence of verbal proficiency, cultural climate, and education level. CFIT is used to measure crystallized ability (a cognitive capability accumulated for a certain amount of time, stored in long-term memory, and called out if needed [31]). This test is used for purposes related to generalized mental ability factors, intelligence, or concentration. CFIT scale division can be seen in Table 2. Some aspects measured in the CFIT sub-test can be seen in Table 3. The CFIT test classification is divided into seven types, as shown in Table 4 related to the CFIT IQ class [32].

TABLE II
SCALE OF CFIT

Scale	Description
Scale 1	Age 4-8 and person with RM. There is no form about A and B. Scale 1 consists of eight subtests of T.
Scale 2	Age 8-15 years. This test is intended for adults who have below-than-normal intelligence. The problem consists of two types: question A and B. Scale 2 consists of four T subtests.
Scale 3	Third scale for the age of > 15 years (for high school age above). The test is aimed at adults with high intelligence. The problem consists of two types: A and B. Scale 3 consists of four T subtests.

TABLE III
SUBTEST OF CFIT

Subtest	Description
Subtest 1	Systematical thinking, is the ability to think sequentially to understand a series of fundamental sustainable problems.
Subtest 2	Sharp differentiation, is the ability to observe the details sharply and think critically to identify the problem.
Subtest 3	Problems association, is the ability to analyze-syntheses to connect two or more similar problems.
Subtest 4	Understanding the concept, is the ability to understand a principle to be applied to different situations.

TABLE IV
CFIT CLASS CATEGORIES BASED ON IQ SCORE

Level	IQ Score	Category
1	> 170	Genius
2	140-169	Very Superior
3	120-139	Superior
4	110-119	High Average
5	90-109	Average
6	80-89	Low Average
7	70-79	Borderline
8	< 79	Mentally Defective

G. Concentration

Research [34] has stated that concentration is the ability to focus on an activity/excitement at a certain time. Several factors affect and inhibit a person's concentration. Table 5 shows the Concentration Factor.

TABLE V
FACTOR OF CONCENTRATION

Influence	Retardant
The level of interest in the activity.	Too much activity.
The readiness of one's mind an activity.	Tension the activity.
A person's ability to select relevant or irrelevant activities.	Physical or psychic fatigue.

Concentration while studying and doing other activities is important because it is a major factor in achieving good study achievement. The environment can affect the ability to concentrate. Each person can have a different way of concentrating. Some people can concentrate while listening to music, studying in a crowd, or being with friends [33]. However, others may need to concentrate in a quiet and soundless environment or have a certain study habit. Sexual intercourse is also influential while concentrating on learning or doing activities. Addiction to playing gadgets can affect one's attitude and behavior. People addicted to gadgets will lose the passion and motivation to learn. Hence, it will also affect their level of concentration.

III. Results and Discussion

A. *Results*

1) Fast Fourier Transform and Normalized

A feature extraction process will be performed on the collected EEG data to get the average peak-to-peak signal [35]. Feature extraction was done by applying the FFT method. This method allows the processed EEG data to get the amplitude peak of each signal. Fig. 3 shows the raw signal as the original brainwave signal. The X-axis represents time, and the Y-axis represents the amplitude of the signal. Fig. 4 shows the signal spectrum processing, converting the original signal to a spectrum displaying amplitudes in a frequency function. In this figure, the X-axis represents the frequency (Hz), and Y-axis represents the amplitude. Meanwhile, Fig. 5 shows the obtained peak signals and the process of getting the peak values. Similar to Fig. 6, the X-axis and Y-axis in Fig. 7 represent frequency (Hz) and amplitude, respectively.

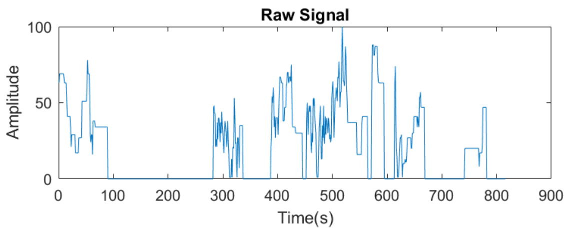


Fig. 3. Raw Signal

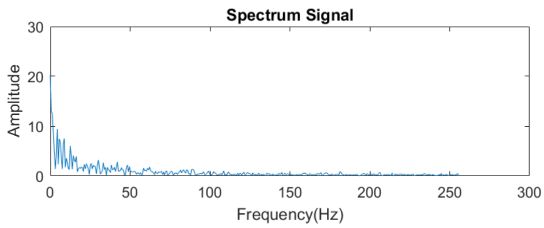


Fig. 4. Spectrum Signal

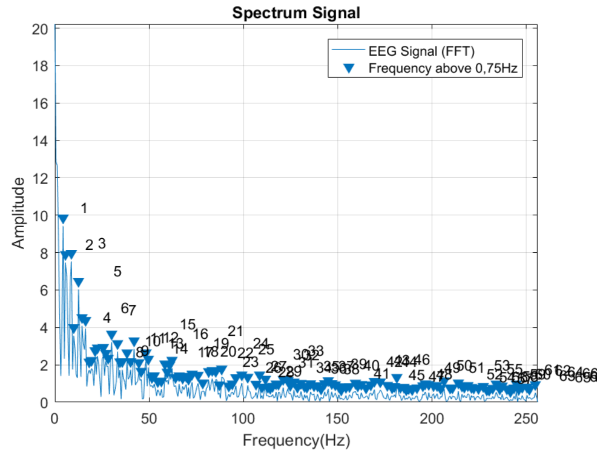
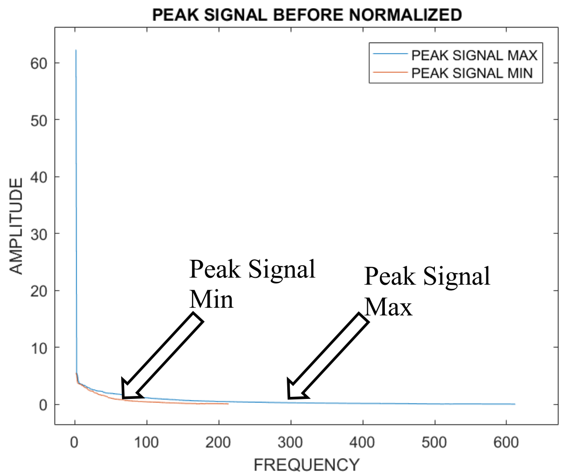
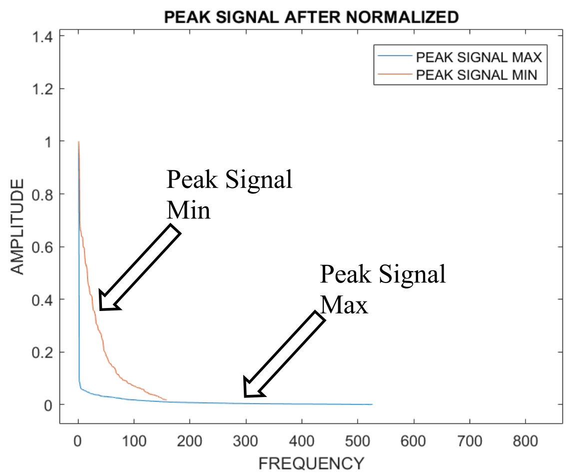


Fig. 5. Peak Signal

Fig. 6(a) shows the peak signal after FFT was performed. Meanwhile, Fig. 6(b) shows the result of the normalization process with a range of values from 0 to 1. Fig. 7(a) shows the removing process of unnecessary signal data with low frequency. Fig. 7(b) shows the final result after removing unnecessary signal data and determining the average signal peak with the highest peak as 1 and the lowest as 0. The normalization is applied to get the average amplitude of peak signals.

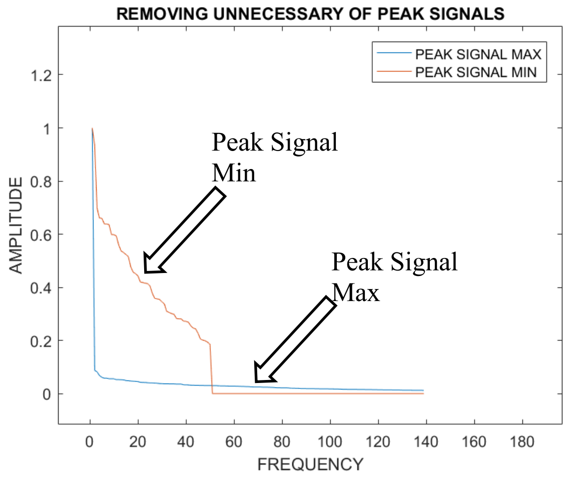


(a)

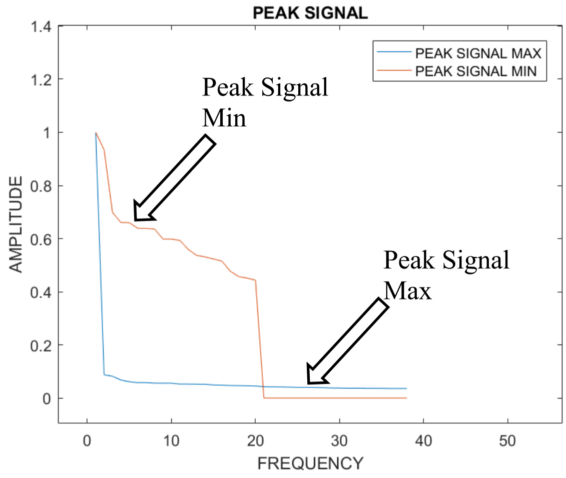


(b)

Fig. 6 Peak Signal FFT (a) Before Normalized and (b) After Normalized



(a)



(b)

Fig. 7 Average Peak Process (a) Remove Unnecessary Signal and (b) Peak Signal

2) *Algorithm Performance*

The performance of the classification algorithm is generally examined by measuring the accuracy of the classification. In this study, K-Nearest Neighbor is applicable, and good results can be obtained. The algorithm is used to obtain a relation pattern and accelerate the detection of brain concentration and learning outcomes. It was classified with an accuracy of 94.59% using K-Fold Cross Validation with the value of K equal to 11, and 117 participants were involved.

B. *Discussions*

A learning outcome is an essential part of learning. A student learning outcome is defined as a change in behavior as learning outcomes in a broader sense include cognitive, affective, and psychomotor fields. Research [36] also states that learning outcomes are the result of teaching and learning interactions. From the teacher's perspective, the act of teaching ends with the process of evaluating learning outcomes. From the student's side, learning outcomes are the end of teaching and the peak of the learning process. Benjamin S. Bloom [37] states six types of behavior in the cognitive category. In Fig. 8, we can see a description of Bloom's Taxonomy.

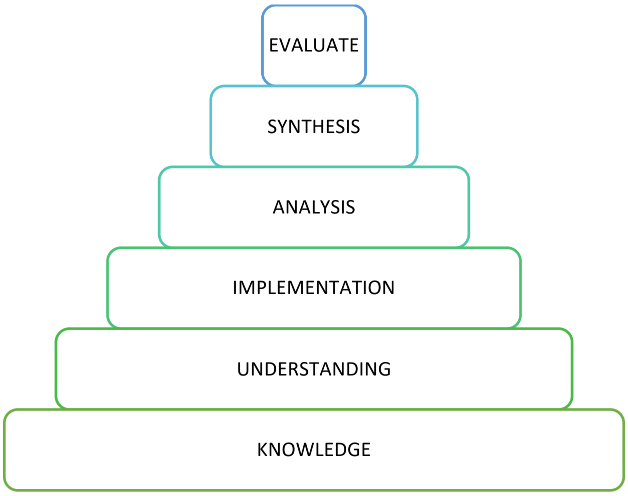


Fig. 8. Bloom Taxonomy

Based on the understanding of learning outcomes mentioned in Fig. 9, it can be concluded that learning outcomes are abilities possessed by students after receiving their learning experiences. Learning outcomes can be assessed through evaluation activities, which are aimed to obtain evidence indicating students' level of ability and understanding in achieving learning objectives.

Fig. 10. Shows the Average Peak Signal. The maximum signal with a test using CFIT shows a value of 0.421, while the CFIT minimum signal is 0.112. Test results with CT have a maximum average value of 0.471 and a minimum average value using CT of 0. The average concentration obtained in subjects tested under CFIT shows a value of 0.214, and the average concentration tested with CT shows a value of 0.246. So, it can be concluded that the subject has a low concentration level. In Fig. 11(a), the CFIT score shows the highest score as 154, and the lowest score is 52, with an average CFIT score of 93. Based on the obtained results, the subject has a low analytical ability, which affects the subject's tendency to solve the problem. In Fig. 11(b), the CT score shows the highest score in CT is 90, and the lowest score is 30, with an average CT score of 57. The test items are the last seven items used to measure the subject's readiness to conduct the Final Examination. The average CT score has a low tendency, so it needs to be evaluated to prepare subjects to get maximum results during the Final Examination.

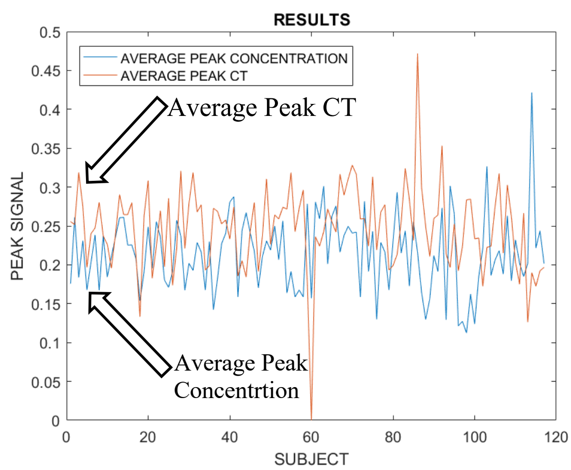
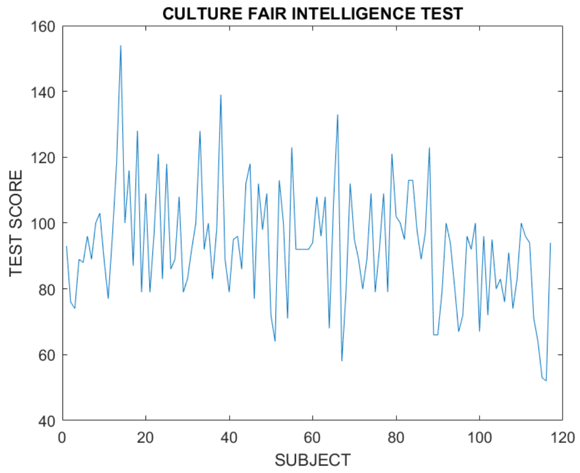
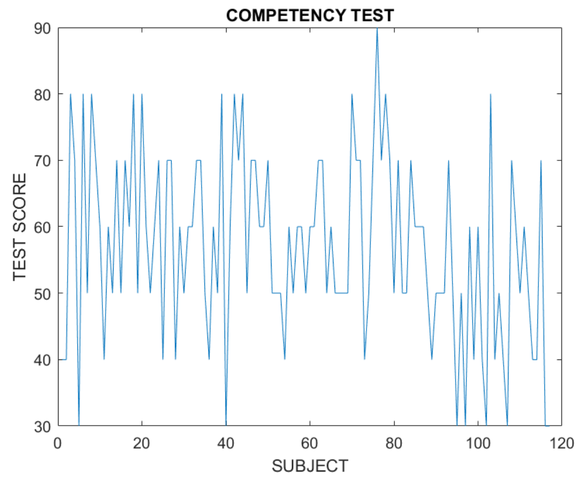


Fig. 9. Average Peak Signal: Concentration (CFIT) and Competency Test (CT)



(a)



(b)

Fig. 10. IQ Test Results (a) CFIT (b) Competency Test

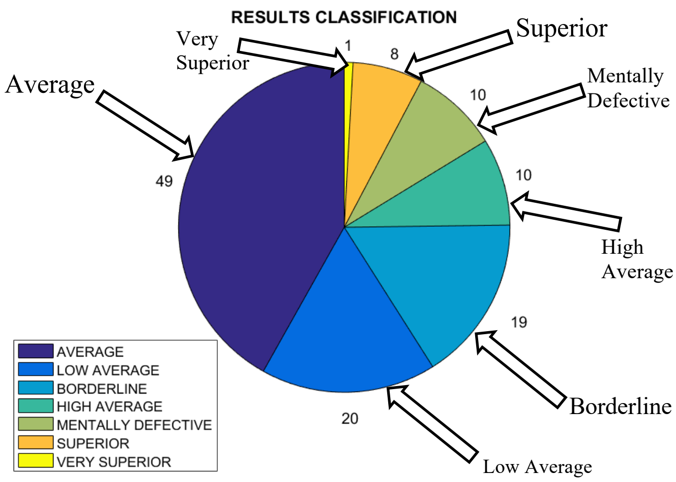


Fig. 11. Classification of IQ Scores

Based on Fig. 11, most of the tested participants are in *Average* classification, with 49 participants belonging to this category. Meanwhile, there are 20 participants in the second category, *Low Average*. Whereas in the *Borderline* category, 19 participants belonged. The same number of participants belonged to the fourth and fifth categories, *High Average* and *Mentally Defective*; each category belonging to 10 participants. In the *Superior* category, there were eight participants. Next, the *Very Superior* category belongs to one participant. While in the last category, there was none participant categorized as *Genius*. Based on the classification that has been done, it can be concluded that participants have a low tendency to concentrate on cognitive activities, so it is necessary to evaluate learning activities to create better results.

IV. Conclusions

Based on the results of research conducted on 117 participants, it was found that brain waves can accelerate the time in detecting concentration through CFIT on learning outcomes through CT. This research is based on patterns obtained through the peak of the FFT. A manual CFIT assessment will take three days to determine one's concentration, while using this system can accelerate 3x faster results than a manual CFIT assessment. This study also showed that the average signal concentration when testing using CFIT showed a value of 0.214, and when using CT was 0.246. The CFIT score has an average of 93 and an average CT score of 57. These results indicate that participants have a low level of concentration. Interviews with psychologists reinforce these results that someone with low-value school subjects does not mean that they are less intelligent. In addition, several factors may influence the result, for example, personal interest in the lessons. By using KNN, the accuracy obtained is 94.59%. Thus, it means the concentration is needed when conducting cognitive activities, both in learning and working to support better results.

References

[1] S. Shrader *et al.*, "Instructional design and assessment: Using communication technology to enhance interprofessional education simulations," *Am. J. Pharm. Educ.*, vol. 80, no. 1, 2016, doi: 10.5688/ajpe80113.

[2] S. J. Deeley, "Using technology to facilitate effective assessment for learning and feedback in higher education," *Assess. Eval. High. Educ.*, vol. 43, no. 3, pp. 439–448, 2018, doi: 10.1080/02602938.2017.1356906.

[3] K. K and S. A, "A Mobile based Intelligent Question Answering System for Education Domain," *Int. J. Inf. Eng. Electron. Bus.*, vol. 10, no. 1, pp. 16–23, 2018, doi: 10.5815/ijieeb.2018.01.03.

[4] L. Sana, K. Nasir, A. Urooj, Z. Ishaq, and I. A. Hameed, "BERS: Bussiness-Related Emotion Recognition System in Urdu Language Using Machine Learning," *Proc. - 2018 5th Int. Conf. Behav. Econ. Socio-Cultural Comput. BESC 2018*, pp. 238–242, 2018, doi: 10.1109/BESC.2018.8697243.

[5] Z. J. H. Tarigan, W. Suprapto, and S. R. Basana, "The Influence of the Corporate Management Commitment in Building Organizational Culture and Cross-Funtional Integration to Improve Company's Business Performance," *Int. J. e-Education, e-Business, e-Management e-Learning*, vol. 7, no. 3, pp. 202–211, 2017, doi: 10.17706/ijeeee.2017.7.3.202-211.

[6] P. Jayakar *et al.*, "Diagnostic utility of invasive EEG for epilepsy surgery: Indications, modalities, and techniques," *Epilepsia*, vol. 57, no. 11, pp. 1735–1747, 2016, doi: 10.1111/epi.13515.

[7] Y. Lin *et al.*, "Evaluating the Effect of Simultaneous Transcranial Direct Current stimulation and Repetitive Transcranial Magnetic Stimulation on Minimally conscious state by Using EEG and Functional MRI," *Brain Stimul.*, vol. 12, no. 2, pp. 403–404, 2019, doi: 10.1016/j.brs.2018.12.303.

[8] A. W. M. System and G. Zanichelli, "Vital EKG," 2018.

[9] S. Pattnaik, M. Dash, and S. K. Sabut, "DWT-based feature extraction and classification for motor imaginary EEG signals," *2016 Int. Conf. Syst. Med. Biol. ICSMB 2016*, no. January, pp. 186–201, 2017, doi: 10.1109/ICSMB.2016.7915118.

[10] M. Zabihi, A. B. Rad, A. K. Katsaggelos, S. Kiranyaz, S. Narkilahti, and M. Gabbouj, "Detection of atrial fibrillation in ECG hand-held devices using a random forest classifier," *Comput. Cardiol. (2010).*, vol. 44, pp. 1–4, 2017, doi: 10.22489/CinC.2017.069-336.

[11] M. Soufineyestani, D. Dowling, and A. Khan, "Electroencephalography (EEG) technology applications and

available devices," *Appl. Sci.*, vol. 10, no. 21, pp. 1–23, 2020, doi: 10.3390/app10217453.
[12] R. Spataro *et al.*, "Reaching and grasping a glass of water by locked-In ALS patients through a BCI-controlled humanoid robot," *Front. Hum. Neurosci.*, vol. 11, no. March, pp. 1–10, 2017, doi: 10.3389/fnhum.2017.00068.
[13] S. L. Oh, J. Vicnesh, E. J. Ciaccio, R. Yuvaraj, and U. R. Acharya, "Deep convolutional neural network model for automated diagnosis of Schizophrenia using EEG signals," *Appl. Sci.*, vol. 9, no. 14, 2019, doi: 10.3390/app9142870.
[14] A. Anuragi and D. Singh Sisodia, "Alcohol use disorder detection using EEG Signal features and flexible analytical wavelet transform," *Biomed. Signal Process. Control*, vol. 52, pp. 384–393, 2019, doi: 10.1016/j.bspc.2018.10.017.
[15] M. McVoy, S. Lytle, E. Fulchiero, M. E. Aebi, O. Adeleye, and M. Sajatovic, "A systematic review of quantitative EEG as a possible biomarker in child psychiatric disorders," *Psychiatry Res.*, vol. 279, no. July, pp. 331–344, 2019, doi: 10.1016/j.psychres.2019.07.004.
[16] H. Chen, W. Chen, Y. Song, L. Sun, and X. Li, "EEG characteristics of children with attention-deficit/hyperactivity disorder," *Neuroscience*, vol. 406, pp. 444–456, 2019, doi: 10.1016/j.neuroscience.2019.03.048.
[17] D. Gartland and R. Strosnider, "Learning Disabilities and Achieving High-Quality Education Standards," *Learn. Disabil. Q.*, vol. 40, no. 3, pp. 152–154, 2017, doi: 10.1177/0731948717696277.
[18] H. Jebelli, S. Hwang, and S. Lee, "EEG Signal-Processing Framework to Obtain High-Quality Brain Waves from an Off-the-Shelf Wearable EEG Device," *J. Comput. Civ. Eng.*, vol. 32, no. 1, p. 04017070, 2018, doi: 10.1061/(asce)cp.1943-5487.0000719.
[19] A. Azhari and F. I. Ammatulloh, "Classification of Concentration Levels in Adult-Early Phase using Brainwave Signals by Applying K-Nearest Neighbor," *Signal Image Process. Lett.*, vol. 1, no. 1, pp. 14–24, 2019, doi: 10.31763/simple.v1i1.170.
[20] M. Tajdini, V. Sokolov, I. Kuzminykh, S. Shiaeles, and B. Ghita, "Wireless sensors for brain activity—a survey," *Electron.*, vol. 9, no. 12, pp. 1–26, 2020, doi: 10.3390/electronics9122092.
[21] A. Bablani, D. R. Edla, and S. Dodia, "Classification of EEG data using k-nearest neighbor approach for concealed information test," *Procedia Comput. Sci.*, vol. 143, pp. 242–249, 2018, doi: 10.1016/j.procs.2018.10.392.
[22] Y. Li, Y. Yang, J. Che, and L. Zhang, "Predicting the number of nearest neighbor for kNN classifier," *International Journal of Computer Science*, vol. 46, no. 4, pp. 662–669, 2019.
[23] A. K. Jaiswal and H. Banka, "Local pattern transformation based feature extraction techniques for classification of epileptic EEG signals," *Biomed. Signal Process. Control*, vol. 34, pp. 81–92, 2017, doi: 10.1016/j.bspc.2017.01.005.
[24] P. Ozel, A. Akan, and B. Yilmaz, "Synchrosqueezing transform based feature extraction from EEG signals for emotional state prediction," *Biomed. Signal Process. Control*, vol. 52, pp. 152–161, 2019, doi: 10.1016/j.bspc.2019.04.023.
[25] D. Pawar and S. Dhage, "Feature extraction methods for electroencephalography based brain-computer interface: A review," *International Journal of Computer Science,* vol. 47, no. 3, pp. 501–515, 2020.
[26] M. K. Delimayanti *et al.*, "Classification of brainwaves for sleep stages by high-dimensional FFT features from EEG signals," *Appl. Sci.*, vol. 10, no. 5, 2020, doi: 10.3390/app10051797.
[27] J. Sun *et al.*, "A hybrid deep neural network for classification of schizophrenia using EEG Data," *Sci. Rep.*, vol. 11, no. 1, pp. 1–16, 2021, doi: 10.1038/s41598-021-83350-6.
[28] G. Deng, "Fast algorithm for zero-phase linear filter using discrete cosine transform," *Electron. Lett.*, vol. 55, no. 10, pp. 621–623, 2019, doi: 10.1049/el.2019.0166.
[29] E. Yudaningtyas, D. H. Santjojo, W. Djuriatno, I. Siradjuddin, and M. R. Hidayatullah, "Identification of pulse frequency spectrum of chronic kidney disease patients measured at TCM points using FFT processing," *QiR 2017 - 2017 15th Int. Conf. Qual. Res. Int. Symp. Electr. Comput. Eng.*, vol. 2017-Decem, pp. 169–172, 2017, doi: 10.1109/QIR.2017.8168476.
[30] A. Azhari and D. P. Ismi, "Lack of knowledge matching algorithms using distance measurements on brainwave features," *IOP Conf. Ser. Mater. Sci. Eng.*, vol. 403, no. 1, 2018, doi: 10.1088/1757-899X/403/1/012080.
[31] D. Li, T. Liu, X. Zhang, M. Wang, D. Wang, and J. Shi, "Fluid intelligence, emotional intelligence, and the Iowa Gambling Task in children," *Intelligence*, vol. 62, no. April, pp. 167–174, 2017, doi: 10.1016/j.intell.2017.04.004.
[32] R. B. Cattell, "The Measurement of the Healthy Personality and the Healthy Society," *Couns. Psychol.*, vol. 4, no. 2, pp. 13–18, 1973.
[33] E. Anatol, "Munich Personal RePEc Archive Studying the banking industrys stability trought market concentration indices STUDYING THE BANKING INDUSTRY' S STABILITY THROUGH MARKET CONCENTRATION," no. 97387, 2019.
[34] B. Yang, Z. Yao, H. Lu, Y. Zhou, and J. Xu, "In-classroom learning analytics based on student behavior, topic and teaching characteristic mining," *Pattern Recognit. Lett.*, vol. 129, pp. 224–231, 2020, doi: 10.1016/j.patrec.2019.11.023.
[35] Y. Wang, Y. Wang, and Q. Shi, "Optimized signal distortion for PAPR reduction of OFDM signals with IFFT/FFT complexity via ADMM approaches," *IEEE Trans. Signal Process.*, vol. 67, no. 2, pp. 399–414, 2019, doi: 10.1109/TSP.2018.2880711.
[36] O. Weiser, I. Blau, and Y. Eshet-Alkalai, "How do medium naturalness, teaching-learning interactions and Students' personality traits affect participation in synchronous E-learning?," *Internet High. Educ.*, vol. 37, no. September 2017, pp. 40–51, 2018, doi: 10.1016/j.iheduc.2018.01.001.
[37] J. B. Arneson and E. G. Offerdahl, "Visual literacy in bloom: Using bloom's taxonomy to support visual learning skills," *CBE Life Sci. Educ.*, vol. 17, no. 1, 2018, doi: 10.1187/cbe.17-08-0178.

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