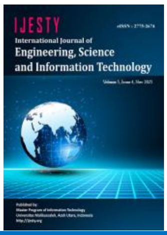
International Journal of Engineering, Science and Information Technology
Volume 5, No. 4 (2025) pp. 297-304
eISSN: 2775-2674
Website: http://ijesty.org/index.php/ijesty
DOI: https://doi.org/10.52088/ijesty.v5i4.1068
Research Paper, Short Communication, Review, Technical Paper




# EEG-Based Focus Analysis to Evaluate the Effectiveness of Active Learning Approaches

**I Putu Agus Eka Darma Udayana[1]*, Made Sudarma[2], I Ketut Gede Darma Putra[2], I Made Sukarsa[2], Minho Jo[3]**

[1]*Department of Technology and Informatics, Indonesian Institute of Business and Technology, Denpasar, Indonesia*
[2]*Department of Engineering Science, Faculty of Engineering, Udayana University, Denpasar, Indonesia*
[3]*Department of Computer Convergence Software, Korea University, Sejong, South Korea*

**Corresponding Author Email: agus.ekadarma@gmail.com*

*The manuscript was received on 22 February 2025, revised on 15 May 2025, and accepted on 10 August 2025, date of publication 11 November 2025*

## Abstract

Electroencephalography (EEG) has emerged as a non-invasive and objective technique for monitoring brain activity in real time, widely applied to measure cognitive states such as concentration and alertness. Its ability to capture brain responses during learning processes makes EEG a promising tool to evaluate student engagement more accurately than conventional methods. This study investigates the effectiveness of two active learning methods, Project-Based Learning (PjBL) and Problem-Based Learning (PBL), in the context of English tutoring for elementary students using EEG signals as a cognitive indicator. A total of 20 students aged 8–12 years from ThinkerBee Learning Centre Bali participated in the study. EEG data were recorded using the Muse 2 Headband while students completed test-based tasks designed for each learning method. The EEG signals were preprocessed using bandpass filtering, Continuous Wavelet Transform (CWT), and frequency band decomposition. Concentration scores were then calculated using two approaches: a heuristic method based on the Beta/(Theta + Alpha) ratio and a Long Short-Term Memory (LSTM) model. The heuristic method produced average scores of 0.3991 (PjBL) and 0.3822 (PBL), with a 4.42% difference, while the LSTM model showed a more substantial difference, with scores of 0.5454 (PjBL) and 0.4265 (PBL). A Spearman correlation test between EEG-derived scores and students' academic results yielded a perfect correlation value of 1.0000, indicating a strong relationship between cognitive engagement and learning outcomes. These results demonstrate the potential of EEG as a reliable tool for objectively assessing learning effectiveness in primary education contexts.

***Keywords***: *Electroencephalography, Concentration, Learning Method, Long Short-Term Memory, Focus Analysis.*

## 1. Introduction

Electroencephalography (EEG) is a non-invasive neuroimaging technique, performed by placing electrodes on the scalp to record the brain's electrical activity. EEG signals provide important information about the brain's working mechanisms, including the processes of perception, attention, memory, and identification of neurological disorders. Due to its safe and noninvasive nature, EEG has become one of the most popular methods in human brain activity research and can be combined with other imaging technologies such as MRI, fNIRS, and PET for a more thorough understanding of brain function and structure [1]. EEG can record real-time brain wave activity in response to certain stimuli, so it can be used as an objective measurement tool to recognise a person's concentration level. Concentration itself is the ability to focus attention on an object fully, and plays an important role in mind control and memory training [2][3]. However, in practice, EEG signal analysis often faces challenges in the form of artefacts such as eye blinks, muscle movements, and other noise that can interfere with data quality. These artefacts can reduce the accuracy of signal interpretation and affect the analysis results, both in medical contexts and brain-computer interface (BCI) systems [4]. Therefore, a preprocessing step such as bandpass filtering is required to filter the signal within a certain frequency range to remove irrelevant noise. Furthermore, a wavelet transform is used to decompose the signal into the time-frequency domain so that important features of the non-stationary signal can be optimally extracted [5][6][7]. There are various EEG hardware devices that can be used to collect data, where each device has its own features and advantages. One of them is the Muse 2 Headband, a portable EEG device designed to record brain activity in real-time. The device is equipped with four electrodes placed at positions TP9, AF7, AF8, and TP10, following the international 10-20 electrode placement system. The Muse 2 has a sample rate of 256 Hz and a 12-bit sample depth, which enables precise recording of brainwave activity [8]. Each EEG channel has different frequency characteristics, which affect the process of recognising human emotions through brain signals [9]. With the ability of EEG to capture brain activity directly, this technology is starting to be applied in various fields. One form of application is in the field of education to objectively evaluate students' cognitive responses. Compared to conventional evaluations such as written tests or observations, the use of EEG allows real-time measurement of student engagement and concentration during learning. In the learning process, choosing the right learning method greatly affects the effectiveness of student learning. There are two most popular and frequently used methods which are Project-Based Learning (PjBL) and Problem-Based Learning (PBL). Where the difference between the two methods is that the PjBL method emphasizes more on learning through projects that will encourage students to be more active in exploring and completing a project, while the PBL method focuses more on problem-based learning that requires students to find solutions to the challenges given. Both encourage active student engagement, but have different approaches and impacts on the thinking process. Research on the comparison between Project-Based Learning (PjBL) and Problem-Based Learning (PBL) methods has been widely conducted especially at the elementary school level. This approach has proven to be effective in increasing students' active involvement in the learning process. The application of PjBL and PBL methods in various learning contexts has shown potential in promoting in-depth understanding of concepts as well as the development of critical thinking skills [10][11]. One area of learning that has become a major concern is the mastery of English. English has now been classified as a global language and plays an important role in international communication, education, and the world of work. However, not a few students have difficulty in mastering English due to lack of motivation and limited learning environment [4][12]. Therefore, learning English from an early age, especially at the elementary school level, becomes very important to shape students' critical thinking abilities and adaptive skills from the start. Thus, this study aims to compare the effectiveness of PjBL and PBL methods in the context of English learning at the elementary school level by using EEG signals as an objective indicator of students' concentration. The EEG data obtained is analyzed through several preprocessing stages and continued with two calculation approaches, namely brain wave ratio calculation and Long Short-Term Memory (LSTM) model, to obtain concentration scores and evaluate their relationship with students' academic performance.

## 2. Literature Review

### 2.1. Related Research

There have been several studies that evaluate the effectiveness of Project-Based Learning (PjBL) and Problem-Based Learning (PBL) methods [13]. Both methods of thematic learning were integrated with science and Bahasa Indonesia content for 21 fifth-grade students. The results showed that the application of this method increased concept understanding and student involvement in the learning process [14]. A comparative study was conducted on two elementary schools in Klaten with a total of 30 students to assess the effect of PjBL and PBL methods on science learning outcomes. The study used observation sheets and test questions as instruments, and the results showed that both methods had a positive effect on student learning achievement.

On the other hand, the utilisation of EEG technology in education and cognitive psychology has shown progress. Research by [15] utilised EEG signals to evaluate the effect of visual stimulus on impulsive behaviour, with pattern recognition [16] applied a combination of CNN, LSTM, and GRU in EEG signal-based emotion classification and managed to obtain an accuracy of up to 98%. These studies prove that EEG signals can represent cognitive and emotional conditions in real-time.

In processing EEG signals, data pre-processing such as the Bandpass Filtering method is used to filter out noise in certain frequency ranges [17]. Then, the Wavelet Transform is widely used to extract features from non-stationary EEG signals [6]. Although various studies have explored the application of PjBL, PBL, and EEG analysis, no study has specifically applied EEG signal analysis to compare the effectiveness of PjBL and PBL learning methods specifically in the context of English language education at the elementary school student level. Therefore, this research is expected to fill the gap with a deep learning-based approach to objectively evaluate students' cognitive responses.

### 2.2. Electroencephalography

It is a technology that describes the electrical activity of the brain, which is very useful for clinical diagnosis and electrophysiological analysis of the brain. Neurons, the basic functional units in the brain, are located in the cerebral cortex, which is divided into four main parts: frontal, parietal, temporal, and occipital. Each of which is responsible for various functions, such as visual information processing by the occipital lobe and auditory perception by the temporal lobe. EEG activity is recorded from a system of electrodes placed on the scalp, reflecting cervical rhythms as a result of the electrical activity of thousands of neurons [18]. An electroencephalogram (EEG) is a brain signal that is obtained non-invasively and used in Brain-Computer Interface (BCI) technology to control external devices [19]. In general, human brain waves change when in normal conditions and when doing activities. The waves recorded by the EEG are the result of mixing several oscillations that appear simultaneously at different frequencies. To see the amplitude of each wave (band power), a mathematical calculation process is carried out through Fourier transform analysis, which will be explained in more detail in the feature extraction section [20][21].

### 2.3. Frequency Band EEG

Brainwaves are electrical waves emitted by the neurons of the brain, with different characteristics that indicate a person's activity or mental state [22]. Delta waves (0.1-3 Hz) appear when a person is sleepy or in deep sleep without dreams. Theta waves (4-7 Hz) are dominant when a person experiences decreased concentration, mild drowsiness, stress, or light sleep. Alpha waves (8-15 Hz) appear when a person is conscious with eyes closed and in a relaxed state. Beta waves (16-30 Hz) are dominant when a person is thinking or fully awake with high mental activity. Meanwhile, gamma waves (30-100 Hz) appear when a person is in a state of full consciousness and experiences very high mental activity, such as performing in public, panic, or fear [23][24].

# 3. Method

## 3.1. Research Design

In this research, the authors focused on comparing two learning methods, namely Project-Based Learning (PjBL) and Problem-Based Learning (PBL), in the context of English language learning at the primary school level. The research subjects consisted of 20 students ranging in age from 8 to 12 years old. Each student took two types of tests specifically designed based on the characteristics of each learning method. The PjBL-based test was structured to enable students to complete project-based tasks, while the PBL-based test focused on problem solving. Both tests aimed to measure the students' level of conceptual understanding and cognitive engagement after learning. During the test, students' brain activity was recorded using the Muse 2 Headband device to capture brain wave patterns under different learning conditions. The final objective of this research is to deliver evidence-based recommendations for educators regarding the selection of learning methods that are more effective in enhancing students' cognitive processes. The research framework, including testing and data collection, is presented in Figure 1.

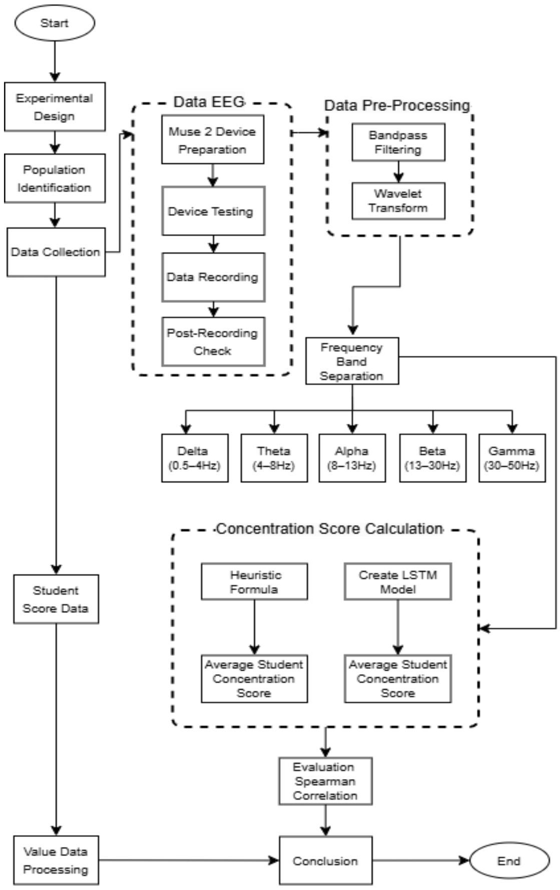



**Fig 1.** Research Method

## 3.2. Preprocessing Signal EEG

The EEG signal obtained from the Muse 2 Headband device is a raw signal containing noise such as artefacts of muscle movement, breathing, or electrical interference from the environment. Therefore, the first step in pre-processing is to apply a bandpass filter with a specific frequency range, such as 0.5-35 Hz or 1-40 Hz, to remove low and high frequency noise so that the resulting signal is more relevant for analysis. In addition, the artefact rejection process is also important to ensure that the analysed EEG data really comes from neural activity, not from disturbances such as body or eye movements [5] [25]. The transfer function of this filter is expressed mathematically as

$$H(f) = \begin{cases} 1 \; untuk \; f_1 \le f \le f_2 \\ 0 \; untuk \; f < f_1 \; atau \; f > f_2 \end{cases} \tag{1}$$

with $f_1$ = 1Hz and $f_2$ = 40Hz [30].

After the bandpass process is complete, the EEG signal is then extracted using Continuous Wavelet Transform (CWT). CWT is a method of signal decomposition into the time-frequency domain that enables detailed analysis of non-stationary signals such as EEG. Different from the Fourier transform, which uses an infinitely long basis function, CWT uses a localised wavelet function, which allows tracking frequency changes locally over time. Mathematically, this process is formulated as [26][27].

$$\gamma(\tau, s) = \int_{s,\tau} f(t)\Psi * (t)dt \tag{2}$$

In this study, the complex Morlet wavelet (cmor) is used to analyse EEG signals per second (256 samples). This process produces CWT coefficients, which represent the energy level on a certain scale. The results of the CWT coefficients will later be grouped into the five main frequency bands of EEG, namely Delta, Theta, Alpha, Beta, and Gamma. This grouping is done based on mapping the CWT scale to the frequency range, then calculating the mean power in each band. This value is used as the input feature for the modelling stage.

## 3.3. Concentration Score Calculation Method

In this study, there are two approaches used to calculate student concentration scores based on EEG data, namely the brainwave ratio-based heuristic method and the Long Short-Term Memory (LSTM) model-based method. Concentration can be measured and analysed through EEG signals, specifically by looking at brain wave activity at beta frequencies related to focus and attention [28]. The first approach uses the EEG band ratio formula that is commonly used in various neurocognitive studies. The formula used is:

$$Concentration = \frac{\beta}{\alpha + \theta} \quad (3)$$

This formula states that the level of concentration is positively correlated with the dominance of beta (β) waves associated with focus and alertness, and decreases as theta (θ) and alpha (α) waves associated with relaxation or sleepiness increase. So, the greater the value of beta compared to alpha + theta, the higher the concentration level is assumed to be. The second approach uses the Long Short-Term Memory (LSTM) machine learning model to perform concentration score estimation based on EEG features. LSTM is a variant of the Recurrent Neural Network (RNN) that can learn patterns from sequential data through an internal long-term memory mechanism [29], [30]. Fig. 2 shows the architecture of the Long Short-Term Memory (LSTM) network, which consists of three main components, namely the Forget Gate, Input Gate, and Output Gate.

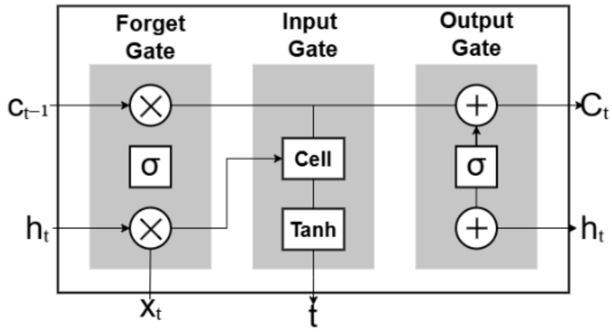



**Fig 2.** LSTM Architecture

LSTM modelling is processed using three frequency bands, namely Beta, Theta, and Alpha. The data is normalised with MinMaxScaler and formatted into three dimensions as model input. The LSTM model consisted of one layer with 64 units, 0.2 dropout, and one output layer with sigmoid activation. The target (label) was coded as 0 for PBL and 1 for PPA. The training process was conducted for 50 epochs with binary_crossentropy as the loss function and Adam as the optimiser. After the model has been trained, the model is saved in .h5 format and reused in the testing stage and processed with a similar format, and then predicted using the model. The prediction results will be in the form of probabilities for each class and then converted to binary labels (PBL/PjBL), and the average prediction value for each class is calculated.

## 3.4. Evaluation

In this study, two approaches were taken to measure the effectiveness of PBL and PjBL learning methods through EEG signal analysis. The first approach uses the Spearman Correlation test, which is a non-parametric statistical method used to determine the level of relationship between two or more ordinal-scale variables. This test does not require the data to be normally distributed, making it suitable for use on ranked or ordinal data. The Spearman correlation coefficient ranges from -1 to +1, where a value of -1 indicates a perfect negative correlation and +1 indicates a perfect positive correlation [31][32]. The second approach focuses on evaluating Long Short-Term Memory (LSTM) models using several standard classification metrics, namely accuracy, precision, recall, and F1-score. These metrics provide a quantitative overview of the model's performance in making accurate and consistent predictions on both training and test data [33]. Thus, this evaluation allows us to assess the extent to which the model is able to differentiate brain activity patterns between students following PBL and PPA methods. Although the model is not intended for classification as an end goal, evaluation of model performance is still important to ensure that the model has a decent predictive quality and can be relied upon as a concentration estimation tool. By using these two evaluation approaches, the research was able to provide a comprehensive picture of the accuracy of concentration estimation from EEG signals as well as the validity of the relationship between brain concentration and student learning outcomes.

# 4. Results And Discussion

## 4.1. Brainwave Classification Results

The following is the average bandpower value obtained from the EEG recordings of each student. The values are the average results of Alpha, Beta, Theta, and Delta waves, which have been preprocessed using a Bandpass Filter and Wavelet Transform. Although the original data includes many timestamps for each band, in this section, only the average of each band for each student is presented.

**Table 1.** Average EEG Signal of PBL Method Students

| Siswa | Average EEG Signal Result | | | | |
|---|---|---|---|---|---|
| | Alpha | Beta | Theta | Delta | Gamma |
| 1 | 46191.1032 | 22994.0859 | 94963.0442 | 98008.3202 | 44542.0516 |
| 2 | 15072.3185 | 10174.7435 | 31333.4338 | 34626.1415 | 16969.3514 |
| 3 | 8106.7846 | 2548.6798 | 23148.1462 | 32231.2776 | 15323.2150 |
| 4 | 101637.340 | 37709.3974 | 227798.305 | 253800.408 | 95426.6250 |
| 5 | 6612.5193 | 8069.5497 | 10859.8463 | 8865.6715 | 3801.2805 |
| 6 | 5373.5746 | 6681.0621 | 8873.7790 | 8432.6425 | 4141.7742 |
| 7 | 9358.7261 | 3791.7772 | 14879.1856 | 18778.8402 | 9486.8773 |
| 8 | 7696.1623 | 5220.9710 | 12518.0923 | 14177.0275 | 7787.8702 |
| 9 | 7531.7086 | 3831.8057 | 12680.9716 | 14292.8462 | 8237.4352 |
| 10 | 8917.5190 | 5624.3083 | 14402.5178 | 16844.9024 | 8756.9433 |
| 11 | 9212.1254 | 5585.2867 | 15346.7991 | 17569.5436 | 9264.5833 |
| 12 | 10236.9320 | 6096.7101 | 17023.0101 | 19260.5823 | 10341.7634 |
| 13 | 7728.7453 | 4301.2410 | 13690.1734 | 15814.2704 | 8342.1806 |
| 14 | 9670.7257 | 5032.7127 | 16890.9472 | 19374.2306 | 9762.4139 |
| 15 | 9612.6524 | 4893.8804 | 16238.1175 | 18435.3485 | 9578.8774 |
| 16 | 9782.3659 | 4930.8998 | 16857.1434 | 19190.5717 | 9854.2175 |
| 17 | 9117.6758 | 5134.0498 | 16145.2489 | 18301.9058 | 9428.0601 |
| 18 | 10726.6107 | 6084.0135 | 18544.4783 | 20684.5792 | 10506.2181 |
| 19 | 10513.2707 | 5753.2311 | 18108.5862 | 20039.7693 | 10062.2186 |
| 20 | 10122.7894 | 5678.4430 | 17262.4771 | 19088.8461 | 9765.1460 |

Table 1 displays the average results of EEG signals from 20 students who participated in Problem-Based Learning (PBL). Table 2 contains the same results but for students who participated in Project-Based Learning (PJBL).

**Table 2.** Average EEG Signal of PjBL Method Students

| Student | Average EEG Signal Result | | | | |
|---|---|---|---|---|---|
| | Alpha | Beta | Theta | Delta | Gamma |
| 1 | 22195.7112 | 18584.7083 | 29648.0057 | 38126.1325 | 18735.2968 |
| 2 | 25261.3929 | 13954.6114 | 51743.2085 | 54616.2848 | 26438.4570 |
| 3 | 22565.4369 | 7796.7128 | 56369.1719 | 68200.6548 | 30233.0054 |
| 4 | 71685.1188 | 32782.6917 | 124356.892 | 121477.497 | 52827.2759 |
| 5 | 5411.7168 | 9116.7371 | 7627.6671 | 6883.8032 | 3820.1389 |
| 6 | 20153.7118 | 10314.1954 | 40387.6792 | 48242.0937 | 18909.3750 |
| 7 | 4392.1900 | 6422.7353 | 6622.8133 | 6580.2352 | 3529.2980 |
| 8 | 26104.9001 | 12783.7981 | 52822.6025 | 62449.5963 | 22947.2910 |
| 9 | 6376.3193 | 5543.0417 | 9070.0166 | 8995.9520 | 4842.6325 |
| 10 | 6257.8614 | 3920.7443 | 9605.4276 | 9760.5675 | 4530.3702 |
| 11 | 7785.0844 | 6181.5117 | 11932.7498 | 13531.3846 | 6580.1694 |
| 12 | 5327.0912 | 4245.1301 | 8093.8777 | 9276.4819 | 4302.1564 |
| 13 | 9040.6227 | 4457.2760 | 15324.9677 | 18279.8284 | 9361.8592 |
| 14 | 9057.4156 | 4834.3430 | 14485.9492 | 17467.9805 | 8784.7593 |
| 15 | 10219.4384 | 7114.4087 | 17299.0641 | 21232.2411 | 10865.4937 |
| 16 | 6567.4529 | 5041.1547 | 11555.7487 | 13200.4811 | 6975.6606 |

| Student | Average EEG Signal Result | | | | |
|---|---|---|---|---|---|
| | Alpha | Beta | Theta | Delta | Gamma |
| 17 | 7473.0886 | 4362.2452 | 12676.2158 | 14768.8643 | 7642.9098 |
| 18 | 9505.3554 | 6201.2387 | 15614.8433 | 18036.9970 | 9127.8580 |
| 19 | 10135.7003 | 6518.8018 | 15796.6360 | 18068.0317 | 9607.7785 |
| 20 | 13002.1333 | 8485.9745 | 21608.6998 | 24026.4319 | 12468.3067 |

Through these data, researchers can proceed to the stage of evaluating the level of student concentration by applying two analysis approaches, namely the heuristic approach and the Long Short-Term Memory (LSTM) model. In both approaches, the processed EEG signal data became the main input to assess students' cognitive responses during the PjBL and PBL method-based tests. The heuristic approach is used to calculate concentration scores based on the ratio of certain brainwave bands, while the LSTM model is used to recognise temporal patterns in EEG data to predict concentration levels in a more dynamic and complex manner. These two methods complement each other in providing an objective and comprehensive picture of how each learning approach affects students' brain activity, particularly in terms of cognitive engagement and focus.

## 4.2. Concentration Score Calculation Result (Heuristic Method)

The calculation of concentration scores using the heuristic approach was carried out for each student's EEG data file in two learning methods, namely PBL and PjBL. The calculation results can be seen in Fig. 3.

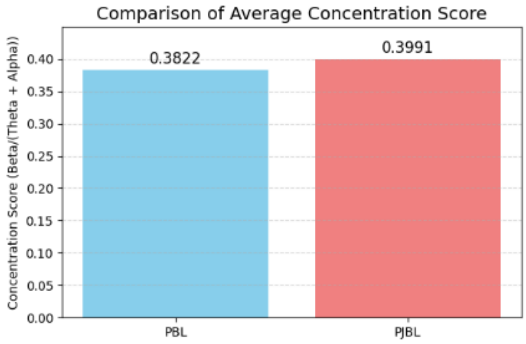



**Fig 3.** Plot Chart of Calculation Results

The figure above shows that the average score of student concentration in the PBL method is 0.3822. While the average score of student concentration in the PjBL method is 0.3991. From this result, it can be seen that the Project-Based Learning (PJBL) method produces a slightly higher concentration score than the Problem-Based Learning (PBL) method. Although the difference is not too large, it indicates that the project-based approach tends to be more able to trigger students' cognitive focus during the problem-solving process.

## 4.3. Concentration Score Prediction Results Using the LSTM Model

After the training and testing process of the Long Short-Term Memory (LSTM) model is completed, the model is used to predict concentration scores based on EEG features consisting of Beta, Theta, and Alpha values. Prediction is done on the test data of students who follow PBL and PJBL learning methods. The prediction results of the model show that the average concentration score of students in the PBL method is 0.4265. While the average student concentration score in the PjBL method is 0.5454. These values are obtained from the average probability of the LSTM model output, where higher values indicate higher concentration predictions from the model on student EEG activity patterns.

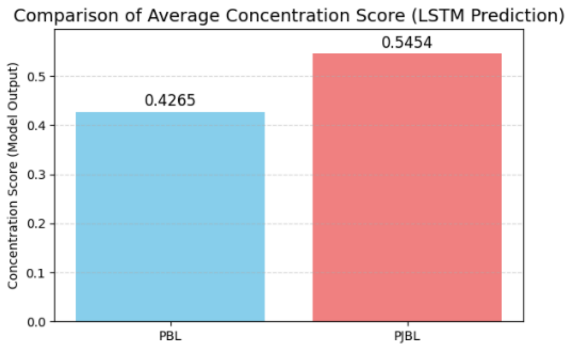



**Fig 4.** Plot Chart of LSTM Model Results

A comparison of the prediction results between the two methods is shown in Fig. 4, where it can be seen that the LSTM model predicts that students who follow learning with the PjBL method have a higher concentration level than students who follow the PBL method. This result supports the trend found for the heuristic approach, but with a larger difference in values. This suggests that the project-based approach not only encourages student engagement conceptually but is also reflected in more focused brain activity patterns as interpreted by the LSTM model.

### 4.4. Evaluation and Discussion of Results

The evaluation of the Spearman Correlation test obtained a Spearman correlation value of 1.0000, which shows a perfect positive relationship between the concentration score obtained and the student's test score. That is, the higher the students' concentration score calculated from the EEG data, the higher the score obtained in the test. This result supports the assumption that focused brain activity (visible from EEG waves) is directly correlated with students' cognitive achievement. An evaluation of the LSTM model performance was conducted to assess its ability to classify PBL and PPA learning methods based on EEG signals. The model was tested using test data and evaluated through classification metrics such as accuracy, precision, recall, and F1-score. The evaluation results show that the model achieved 64.74% accuracy, 64.85% precision, 99.62% recall, and 78.56% F1-score. These metrics show that the model performs well enough to be used as a tool for estimating student concentration based on EEG signal patterns. However, the performance of the model tends to be biased towards the PjBL class, with a high recall value for PjBL but very low for PBL. This can be caused by data imbalance or the EEG patterns of students in the PPA class that are more easily recognised by the model. Nevertheless, the model output can still be used to evaluate the tendency of concentration patterns between learning methods in general.

**Table 3.** Comparison Of Results Based On Heuristic And LSTM Approaches

| Learning Methods | Heuristik | LSTM |
|---|---|---|
| PBL | 0.3822 | 0.4265 |
| PjBL | 0.3991 | 0.5454 |
| Difference (%) | 4.42% | 27.89% |

Overall, the results of this study indicate that the PjBL method is more effective in improving students' learning concentration than PBL. Table 3 shows a comparison of the average concentration scores of students in PBL and PjBL methods based on two approaches, namely heuristic calculation and LSTM model prediction. It can be seen that the concentration score in the PjBL method is higher than PBL in both approaches, with a difference of 4.42% (heuristic) and 23.90% (LSTM).

## 5. Conclusion

The conclusion obtained from this research is that the Project-Based Learning (PjBL) learning method is more effective or slightly superior in improving students' concentration, critical thinking patterns, and cognitive skills, which in this study was conducted on 20 students with an age range of 8-12 years in English language learning. This conclusion is reinforced by the results of the calculation of concentration scores using the heuristic method, which shows that the PJBL method produces higher concentration scores than PBL, with the average difference in student concentration scores in the PjBL and PBL methods being around 4.42%. The results obtained from the LSTM model also show that the PjBL method produces higher concentration scores, with a difference between the average student concentration scores in the PjBL and PBL methods of around 23.90%. In addition, the Spearman correlation test obtained a result of 1.0000 on student test scores, indicating a perfectly strong relationship between brain activity and academic performance. However, the LSTM model used still shows a classification bias towards the PjBL class, so improvements need to be made to the data distribution and model structure. Therefore, future research is recommended to use a larger and more balanced dataset and explore other model architectures to improve generalisation and prediction accuracy.

## Acknowledgement

This research was successfully conducted as planned. The researchers would like to express their sincere gratitude to the Directorate General of Higher Education, Ministry of Education, Culture, Research, and Technology, for providing financial support for this research. Appreciation is also extended to Udayana University and the Indonesian Institute of Business and Technology for facilitating this study by providing the necessary workspace and laboratories equipped with various screen sizes and types for system testing.

## References

[1] A. Chaddad, Y. Wu, R. Kateb, and A. Bouridane, “Electroencephalography signal processing: A comprehensive review and analysis of methods and techniques,” *Sensors*, vol. 23, no. 14, p. 6434, 2023, doi: doi.org/10.3390/s23146434.

[2] L. Xu, X. Xing, J. Chang, and P. Lin, “A Multi-Domain Coupled Spatio-temporal Feature Interaction Model for EEG Emotion Recognition,” *IEEE Trans. Instrum. Meas.*, 2025, doi: 10.1109/TIM.2025.3571107.

[3] B. Zali-Vargahan, A. Charmin, H. Kalbkhani, and S. Barghandan, “Deep time-frequency features and semi-supervised dimension reduction for subject-independent emotion recognition from multi-channel EEG signals,” *Biomed. Signal Process. Control*, vol. 85, p. 104806, 2023, doi: https://doi.org/10.1016/j.bspc.2023.104806.

[4] M. Grobbelaar *et al.*, “A survey on denoising techniques of electroencephalogram signals using wavelet transform,” *Signals*, vol. 3, no. 3, pp. 577–586, 2022, doi: 10.3390/signals3030035.

[5] S. N. S. S. Daud and R. Sudirman, “Wavelet based filters for artifact elimination in electroencephalography signal: A review,” *Ann. Biomed. Eng.*, vol. 50, no. 10, pp. 1271–1291, 2022, doi: 10.1007/s10439-022-03053-5.

[6] O. Almanza-Conejo, D. L. Almanza-Ojeda, J. L. Contreras-Hernandez, and M. A. Ibarra-Manzano, “Emotion recognition in EEG signals using the continuous wavelet transform and CNNs,” *Neural Comput. Appl.*, vol. 35, no. 2, pp. 1409–1422, 2023, doi: 10.1007/s00521-022-07843-9.

[7] Z. Huang and M. Wang, “A review of electroencephalogram signal processing methods for brain-controlled robots,” *Cogn. Robot.*, vol. 1, pp. 111–124, 2021, doi: https://doi.org/10.1016/j.cogr.2021.07.001.

[8] L. F. Morán Mirabal, L. M. Martínez Álvarez, and J. A. Ruiz Ramirez, “Muse 2 headband specifications (neuronal tracking).” Institute for the Future of Education| Living Lab & Data Hub, pp. 1–3, 2022.

[9] Z.-T. Liu, S.-J. Hu, J. She, Z. Yang, and X. Xu, "Electroencephalogram emotion recognition using combined features in variational mode decomposition domain," *IEEE Trans. Cogn. Dev. Syst.*, vol. 15, no. 3, pp. 1595–1604, 2023, doi: 10.1109/TCDS.2022.3233858.

[10] J. Krajcik *et al.*, "Assessing the effect of project-based learning on science learning in elementary schools," *Am. Educ. Res. J.*, vol. 60, no. 1, pp. 70–102, 2023, doi: 10.3102/000283122211292.

[11] R. Amini, B. Setiawan, Y. Fitria, and Y. Ningsih, "The difference of students learning outcomes using the project-based learning and problem-based learning model in terms of self-efficacy," in *Journal of Physics: Conference Series*, 2019, vol. 1387, no. 1, p. 12082. doi: 10.1088/1742-6596/1387/1/012082.

[12] R. Simbolon and H. D. Koeswanti, "Comparison of Pbl (Project Based Learning) models with Pbl (Problem Based Learning) models to determine student learning outcomes and motivation," *Int. J. Elem. Educ.*, vol. 4, no. 4, pp. 519–529, 2020, doi: 10.23887/ijee.v4i4.30087.

[13] T. Setiawan, J. M. Sumilat, N. M. Paruntu, and N. N. Monigir, "Analisis Penerapan model Pembelajaran project based learning Dan problem based learning pada Peserta Didik Sekolah Dasar," *J. Basicedu*, vol. 6, no. 6, pp. 9736–9744, 2022, doi: doi.org/10.31004/basicedu.v6i6.4161.

[14] T. Adicondro and I. Anugraheni, "Pengaruh Problem Based Learning (Pbl) Dan Project Based Learning (PJBL) Terhadap Hasil Belajar Ipa Siswa Sekolah Dasar," *J. Ilm. Wahana Pendidik.*, vol. 8, no. 14, pp. 452–461, 2022, doi: 10.5281/zenodo.7016068.

[15] P. Sarma and S. Barma, "Review on stimuli presentation for affect analysis based on EEG," *IEEE Access*, vol. 8, pp. 51991–52009, 2020, doi: https://doi.org/10.1109/ACCESS.2020.2980893.

[16] G. A. V. M. Giri and M. L. Radhitya, "Electroencephalogram-Based Emotion Classification Using Machine Learning and Deep Learning Techniques," *IJCCS (Indonesian J. Comput. Cybern. Syst.*, vol. 18, no. 3, doi: https://doi.org/10.22146/ijccs.96665.

[17] D. L. Sherman and N. V Thakor, "Eeg signal processing: Theory and applications," in *Neural Engineering*, Springer, 2020, pp. 97–129. doi: 10.1007/978-3-030-43395-6_3.

[18] M. Felja, A. Bencheqroune, M. Karim, and G. Bennis, "Removing artifacts from EEG signal using wavelet transform and conventional filters," *WSEAS Trans. Inf. Sci. Appl.*, vol. 17, pp. 177–183, 2020, doi: 10.37394/23209.2020.17.22.

[19] M. T. Sadiq *et al.*, "Motor imagery EEG signals classification based on mode amplitude and frequency components using empirical wavelet transform," *IEEE access*, vol. 7, pp. 127678–127692, 2019, doi: https://doi.org/10.1109/ACCESS.2019.2939623.

[20] Z. Khakim and S. Kusrohmaniah, "Dasar-Dasar Electroencephalography (EEG) bagi Riset Psikologi," *Bul. Psikol.*, vol. 29, no. 1, pp. 92–115, 2021, doi: 10.22146/buletinpsikologi.52328.

[21] C. Zhang, A. A. Mousavi, S. F. Masri, G. Gholipour, K. Yan, and X. Li, "Vibration feature extraction using signal processing techniques for structural health monitoring: A review," *Mech. Syst. Signal Process.*, vol. 177, p. 109175, 2022, doi: https://doi.org/10.1016/j.ymssp.2022.109175.

[22] M. Priyadarshani, P. Kumar, K. S. Babulal, D. S. Rajput, and H. Patel, "Human brain waves study using EEG and deep learning for emotion recognition," *IEEE Access*, vol. 12, no. 1, pp. 101842–101850, 2024, doi: https://doi.org/10.1109/ACCESS.2024.3427822.

[23] A. D. Wibawa, D. P. Wulandari, P. S. Rahayu, and W. R. Islamiyah, "Statistical analysis of subject-specific EEG data during stroke rehabilitation monitoring," in *2020 10th Electrical Power, Electronics, Communications, Controls and Informatics Seminar (EECCIS)*, 2020, pp. 168–172. doi: https://doi.org/10.1109/EECCIS49483.2020.9263462.

[24] S. Poorani and P. Balasubramanie, "Seizure detection based on eeg signals using asymmetrical back propagation neural network method," *Circuits, Syst. Signal Process.*, vol. 40, no. 9, pp. 4614–4632, 2021, doi: 10.1007/s00034-021-01686-w.

[25] E. Gani, A. Rio, M. Nugraha, and F. Haryanto, "The Effect of Myopia on Brain Signals: Insights from EEG Studies," *J. Penelit. Fis. dan Apl.*, vol. 14, no. 1, pp. 19–32, 2024, doi: https://doi.org/10.26740/jpfa.v14n1.p19-32.

[26] Renuka Nyayadhish et al, "Fake News Detection in Model Integral: A Hybrid CNN-BiLSTM Model," *Int. J. Eng. Sci. Inf. Technol.*, vol. 5, no. 3, pp. 337–343, 2025, doi: 10.52088/ijesty.v5i3.1058.

[27] F. K. Supriyono Supriyono, Aji Prasetya Wibawa, Suyono Suyono, "Enhancing Teks Summarization of Humorous Texts with Attention-Augmented LSTM and Discourse-Aware Decoding," *Int. J. Eng. Sci. Inf. Technol.*, vol. 5, no. 3, pp. 156–168, 2025, doi: 10.52088/ijesty.v5i3.932.

[28] M. S. Dehnavi, V. S. Dehnavi, and M. Shafiee, "Classification of mental states of human concentration based on EEG signal," in *2021 12th International Conference on Information and Knowledge Technology (IKT)*, 2021, pp. 78–82. doi: https://doi.org/10.1109/IKT54664.2021.9685731.

[29] F. Santosa, E. Oktafanda, H. Setiawan, and A. Latif, "Advanced Long Short-Term Memory (LSTM) Models for Forecasting Indonesian Stock Prices," *J. Galaksi*, vol. 1, no. 3, pp. 198–208, 2024, doi: https://doi.org/10.70103/galaksi.v1i3.42.

[30] J. Zhao, X. Mao, and L. Chen, "Speech emotion recognition using deep 1D & 2D CNN LSTM networks," *Biomed. Signal Process. Control*, vol. 47, pp. 312–323, 2019, doi: https://doi.org/10.1016/j.bspc.2018.08.035.

[31] S. Chatterjee, "A new coefficient of correlation," *J. Am. Stat. Assoc.*, vol. 116, no. 536, pp. 2009–2022, 2021, doi: https://doi.org/10.1080/01621459.2020.1758115.

[32] A. de Raadt, M. J. Warrens, R. J. Bosker, and H. A. L. Kiers, *A comparison of reliability coefficients for ordinal rating scales*. Springer, 2021. doi: 10.1007/s00357-021-09386-5.

[33] V. J. Raja, M. Dhanamalar, G. Solaimalai, D. L. Rani, P. Deepa, and R. G. Vidhya, "Machine Learning Revolutionizing Performance Evaluation: Recent Developments and Breakthroughs," in *2024 2nd International Conference on Sustainable Computing and Smart Systems (ICSCSS)*, 2024, pp. 780–785. doi: https://doi.org/10.1109/ICSCSS60660.2024.10625103.