# A Proposed Model for Detecting Learning Styles Based on the Felder-Silverman Model Using KNN and LR with Electroencephalography (EEG)

MS Hasibuan[1,*], R. Rizal Isnanto[2], Deshinta Arrova Dewi[3], Tri Basuki Kurniawan[4], Ming-Lang Yeh[5], Adi Wijaya[6]

[1]*Institute Informatics and Business Darmajaya, Indonesia, Jln ZA Pagar Alam 93 A, Bandar Lampung and 35136, Indonesia*

[2]*University Diponegoro, Jln Imam Bardjo no 5, Semarang and 50241, Semarang*

[3,4]*Faculty of Data Science and Information Technology, INTI International University, Nilai, Malaysia*

[5]*Chung Hua University, Hsinchu, Taiwan, ROC*

[6]*Department of Health Information Management, Universitas Indonesia Maju, Jakarta 12610, Indonesia*

(Received: November 17, 2024; Revised: December 18, 2024; Accepted: January 11, 2025; Available online: March 15, 2025)

**Abstract**

The identification of learning styles plays a crucial role in enhancing personalized education and optimizing learning outcomes. This research proposes a model for detecting learning styles based on the Felder-Silverman model using two machine learning algorithms: K-Nearest Neighbors (KNN) and Linear Regression (LR). Electroencephalography (EEG) data, known for its ability to capture cognitive and neural activity, serves as the primary dataset for this study. The proposed model was tested on a dataset comprising EEG signals collected during various learning tasks. Feature extraction and preprocessing techniques were employed to ensure high-quality input for the learning algorithms. The experimental results revealed that the LR-based model achieved an accuracy of 96.4%, significantly outperforming the KNN-based model, which obtained an accuracy of 89.9%. These findings highlight the potential of EEG-based models for accurately identifying learning styles, offering valuable insights for educators and researchers aiming to implement adaptive learning systems. This study demonstrates the feasibility and effectiveness of combining EEG data with machine learning techniques for learning style detection, paving the way for more personalized and efficient educational approaches. Future research will explore the integration of additional physiological data and advanced machine learning methods to further improve model accuracy and applicability.

*Keywords:* Learning Style, EEG, Felder Silverman, Process Innovation

## 1. Introduction

In the educational process, it is important for educators to understand students' learning styles so that teaching methods can align with each student's individual preferences. Learning style is an individual characteristic that influences how a person receives, processes, and interprets information. One commonly used learning style model is the Felder-Silverman model, which categorizes learning styles into several dimensions, such as processing (active-reflective), perception (sensing-intuitive), input (visual-verbal), and understanding (sequential-global) [1]. Understanding these learning styles can aid in the personalization of learning, thereby enhancing student engagement and learning outcomes. [2], [3], [4].

With the advancement of technology, objectively detecting learning styles using physiological data, such as EEG (electroencephalography) signals, has become an interesting research topic. EEG can capture electrical activity in the brain that reflects various cognitive activities, which are related to individual learning styles[5], [6]. Several studies show that EEG signals can be used to identify patterns related to attention, perception, and information processing that are relevant to the dimensions of learning styles [7], [5], [8]. These studies indicate that there is a correlation between EEG activity in specific brain areas and individual learning style preferences. The use of EEG in detecting learning

***Corresponding author: MS Hasibuan (msaid@darmajaya.ac.id)**
**DOI: https://doi.org/10.47738/jads.v6i2.659**

styles offers a new approach in educational research and neuroscience, potentially providing a deeper understanding of the teaching-learning process. Several studies have examined differences in EEG activity based on learning styles, such as differences in alpha and beta waves associated with visual and verbal processing [7], [9]. In addition, the machine learning approach has also been applied in EEG signal analysis to classify learning styles [8], thereby increasing accuracy in detecting learning styles based on physiological data.

However, research on the use of EEG to detect learning styles based on the Felder-Silverman model is still relatively minimal, especially in the context of education in Indonesia. Therefore, this study aims to explore the use of EEG in detecting learning styles based on the Felder-Silverman model, which is expected to be the basis for the development of a learning personalization system in the future. This study will use the EEG approach to identify learning style preferences on the Felder-Silverman dimensions in the hope of providing a short time for detection and accurate results.

## 2. Literature Review

Learning styles have become a major topic in educational research, particularly because of their role in facilitating more effective learning and personalizing instruction [2], [10], [4]. One well-known learning style model is the Felder-Silverman model, which divides learning style preferences into four dimensions: processing (active-reflective), perception (sensory-intuitive), input (visual-verbal), and comprehension (sequential-global) [1]. This model is widely applied in engineering and science education to help educators understand the diverse cognitive needs of students [11], [12].

Research on the application of the Felder model shows that adapting teaching according to learning styles can increase student motivation and learning outcomes [11]. For example, found that learning style-based instruction in engineering education can improve student engagement and performance [13]. However, the main obstacle in implementing this model is that the learning style identification method still relies heavily on subjective questionnaires, such as the Index of Learning Styles (ILS), which has the potential to cause bias [14], [15]. Table 1 show the FSLS details.

**Table 1.** Felder Silverman Learning Style

| Scale | Item | Factor |
|---|---|---|
| Sensing-Intuitive | 38, 6, 18, 14, 2, 10, 34, 26, 22, 42, 30 | Facts, data, the real or abstraction (theory, models, interpretations) |
| Visual-Verbal | 7, 31, 23, 11, 15<br>27, 19, 3, 3, 35, 43,3 9 | Information Format preferred for input visual<br>Information format preferred for memory or recall |
| Sequential- global | 20, 36, 44, 8, 12, 32, 24<br>28, 4, 16, 40 | Sequential/linear thinking<br>Random/holistic thinking<br>The big picture (the forest) thinking or the tree (detail) |
| Active-reflective | 25, 1, 29, 5, 17<br>37, 13, 9<br>21, 33, 41 | Action-first or reflection<br>Outgoing or reservation<br>Favorable or unfavorable attitude toward group work |

In the last decade, physiological data-based technologies, particularly electroencephalography (EEG), have begun to be explored to overcome the limitations of these subjective methods. EEG is a non-invasive technique that measures the electrical activity of the brain, and has been shown to provide insight into the cognitive processes that occur during learning [16]. EEG is able to capture brain dynamics at certain frequencies that are associated with patterns of attention, perception, and information processing that are relevant to an individual's learning style [7], [17]. For example, alpha waves are often associated with attention and relaxation, while beta waves are associated with intense cognitive activity and focus [9], [18].

Research using EEG to detect learning styles has shown promising results in previous studies. The study identified differences in EEG activity using CNN in students with visual and verbal learning styles, showing that visual learners tend to have higher beta activity when processing visual information compared to verbal learners [19], [20]. Another study showed that alpha and beta waves can differentiate between visual and verbal learning preferences [21]. These findings align with research, which used machine learning methods to classify learning styles based on EEG signals.

ISSN 2723-6471


The use of classification techniques enables more accurate identification of learning styles and can be implemented in real-time educational applications[22], [23].

The use of EEG in education has great potential to optimize the learning process. EEG can provide deep insights into attention patterns, engagement, and learning style preferences that are difficult to identify through conventional methods. However, several challenges are also faced in this research, such as the complex interpretation of EEG signals and the potential noise from environmental factors. To address this, approaches combining EEG with machine learning are increasingly being used to maximize the accuracy of learning style detection [22].

Overall, previous studies show that using EEG to detect learning styles based on the Felder-Silverman model has great potential, although there are still various challenges in the implementation process. Therefore, this research aims to expand studies on detecting Felder-Silverman learning styles using EEG, focusing on improving classification accuracy through machine learning methods. In the future, this study is expected to support the development of adaptive learning systems that can provide more personalized teaching approaches for students.

### 3. Proposed Method

Figure 1 illustrates the proposed framework for learning style detection using EEG signals, as presented below.

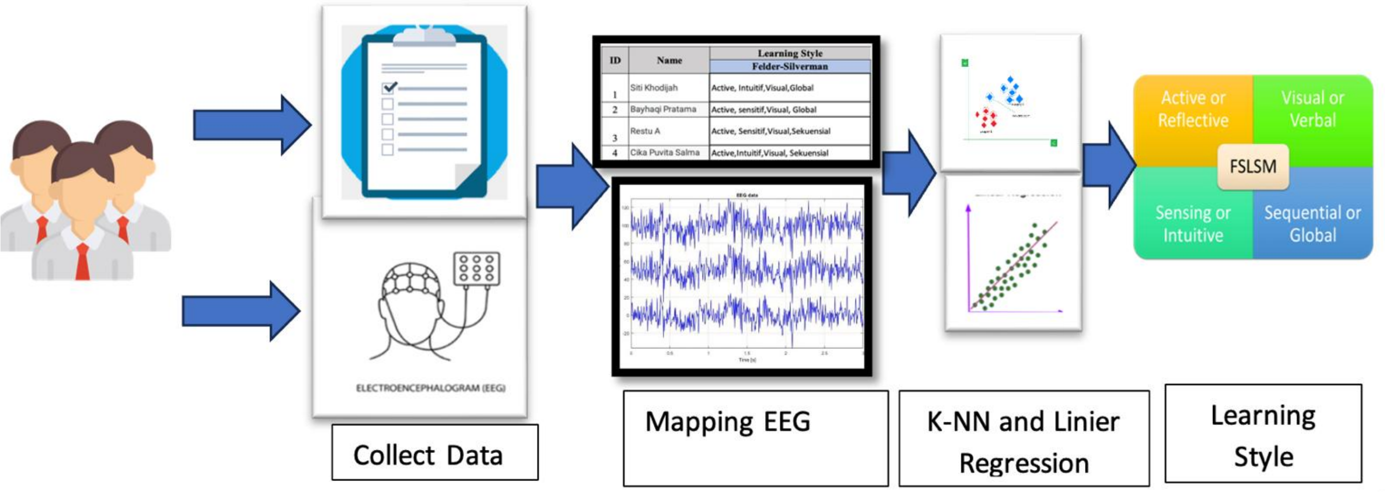


**Figure 1.** Proposed Learning Style Detection EEG

## 3.1. Collect Data

This study involved undergraduate and postgraduate students. The students were selected from the undergraduate program in Informatics Engineering and the Master's program in Informatics Engineering. Before the experiment, participants were asked to complete the ILS to identify their initial learning style preferences within the dimensions of the Felder-Silverman model. Then, EEG data collection was conducted using the Raven's Advanced Progressive Matrices (RAPM) instrument.

This study involved undergraduate and postgraduate students selected from the undergraduate program in Informatics Engineering and the Master's program in Informatics Engineering. The participants taken are limited to undergraduate and postgraduate students. This is based on them already having a basis in the use of technology, because if the participants are outside informatics there are other issues that will be the focus, namely understanding learning tools

Before the experiment, participants completed the Questionnaire to identify their initial learning style preferences within the dimensions of the Felder-Silverman model. Then, EEG data collection was conducted using the RAPM instrument. During the EEG recording, participants were seated comfortably in a quiet room to minimize external distractions. EEG electrodes were placed on specific scalp locations based on the international 10-20 system to capture brain activity related to cognitive processing. Participants were instructed to complete the RAPM questions while their brain signals were continuously recorded.

ISSN 2723-6471


### 3.2. Mapping EEG

The signal obtained from EEG undergoes data preprocessing through noise filtering, artifact removal, and normalization, resulting in cleaner and more accurate data. The mapping is based on previous studies to determine the learning style that matches the obtained signals, where the signals generated through filling in the RAPM are mapped as the learner provides their answers.

### 3.3.Prediction Learning Style Felder Silverman

The Felder-Silverman learning style model classifies learning preferences into four main dimensions: Perception, which consists of Sensing and Intuitive; Input, which includes Visual and Verbal; Processing, which is divided into active and reflective; and understanding, which consists of sequential and global.

## 4. Result and Discussion

### 4.1. Collect Data

Learning Style Detection using a questionnaire successfully collected 100 students as respondents. Furthermore, students will be given Felder Silverman learning style questions which will be the basis for determining learning styles. The following are details of the participant data that have been taken.

The following table 2 contains data related to the research Respondent.

**Table 2.** Data Respondent

| Item | Category | Count | Mean |
|---|---|---|---|
| Gender | Male | 50 | |
| | Female | 50 | |
| Age | | | 25 |
| S1/S2 | S1 | 50 | |
| | S2 | 50 | |

Based on table 2 above, the respondents of this study were 100 students consisting of S1 and S2 students with male and female genders. The following table contains data related to the results of the ILS that have been presented to the respondent.

**Table 3.** Result ILS

| ID | Dimension | | | | | | | | Learning Style |
|---|---|---|---|---|---|---|---|---|---|
| | Active | Reflective | Sensing | Intuitive | Visual | Verbal | Sequential | Global | |
| S2001J | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | Active, Global |
| S2002K | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | Active, Sequence |
| S2003R | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 1 | Reflective, Visual, Global |
| S2004Y | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | Reflective Visual |
| S2005F | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | Sensing, Visual |
| S1001T | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | Active |
| S1002P | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | Global |
| S1003R | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | Visual |

The detection of multiple learning styles, such as active and reflective, indicates that the learner possesses both active and reflective learning styles. Based on the results of the ILS (Index of Learning Styles) assessment, the learner exhibits more than one learning style, as demonstrated in table 3. The following are the results of the data from S1 and S2 student respondents in figure 2

ISSN 2723-6471


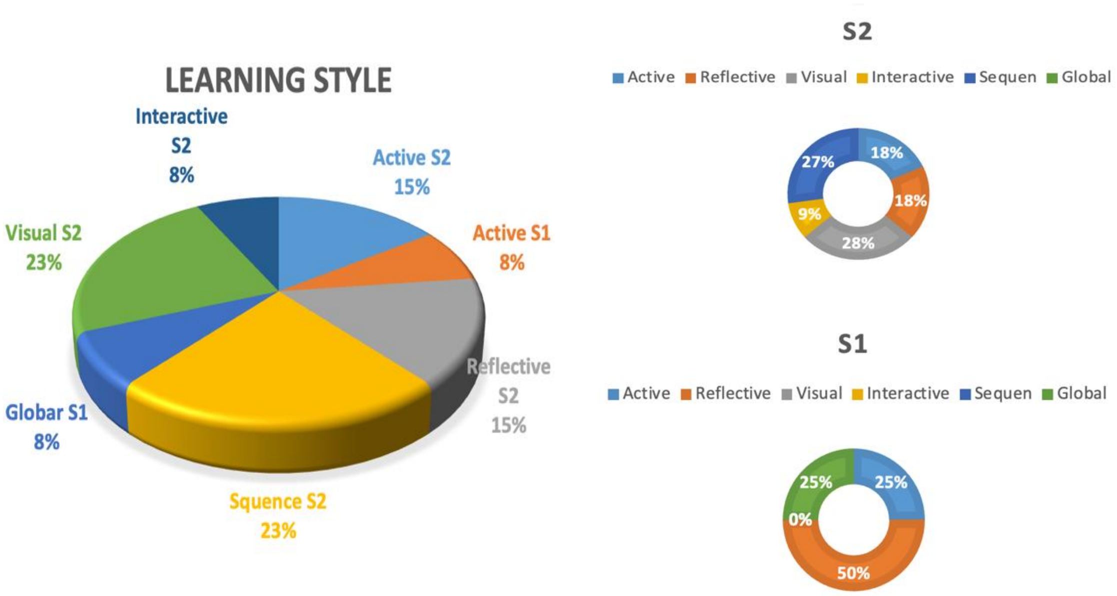


**Figure 2.** Felder Silverman Learning Style Distribution using ILS

The EEG data collection process is carried out through a trigger when filling out questions from RAPM questions which have 36 questions. The RAPM questions given are divided into 4 sessions to ensure the comfort of learners answering the questions. The following is figure 3 related to the RAPM questionnaire.

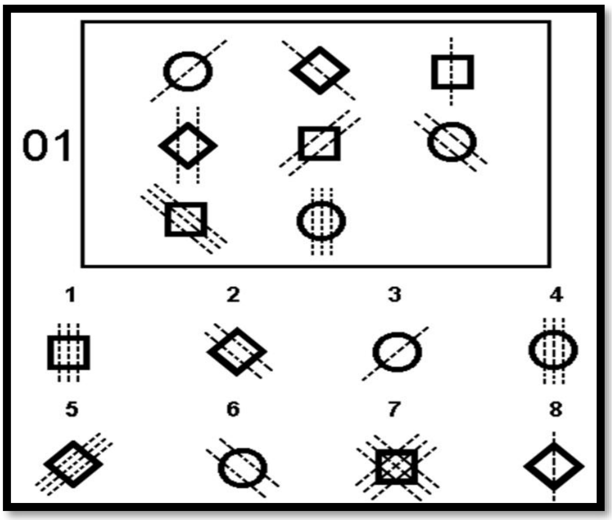


**Figure 3.** RAPM Question

RAPM is a psychological assessment tool designed to measure cognitive abilities and analytical reasoning without reliance on verbal knowledge or specific cultural context, thereby minimizing bias in evaluation. The test consists of a series of incomplete matrices, where participants are required to complete the existing patterns, and it is frequently utilized in educational settings, psychological research, and employee selection processes. The primary benefit of RAPM lies in its capacity to provide an objective assessment of an individual's intellectual potential, aiding in talent identification and offering valuable insights into critical thinking and problem-solving abilities, which are essential across various domains, including education and the workforce. Based on figure 3 which is a RAPM question that has been given to students, the following data has been produced. The following is table 4 regarding the RAPM results from S2001J students.

**Table 4** Result RAPM S2001J and RAPM S1001T

| RAPM S2001J | | | | RAPM S1001T | | | |
|---|---|---|---|---|---|---|---|
| **No** | **Answer** | **Status** | **Time** | **No** | **Answer** | **Status** | **Time** |
| 1 | 3 | False | 12:56:35.020 | 1 | 4 | False | 10:57:50.500 |
| 2 | 1 | True | 12:57:05.780 | 2 | 1 | True | 10:58:18.590 |
| 3 | 7 | True | 12:57:44.040 | 3 | 4 | False | 10:58:52.650 |
| 4 | 4 | True | 12:58:14.860 | 4 | 5 | False | 10:59:21.080 |
| 5 | 1 | False | 12:58:42.410 | 5 | 3 | True | 10:59:53.020 |
| 6 | 1 | True | 12:59:06.480 | 6 | 7 | False | 11:00:21.890 |
| 7 | 2 | False | 12:59:39.790 | 7 | 3 | False | 11:00:21.890 |
| 8 | 8 | False | 13:00:13.420 | 8 | 1 | True | 11:01:25.790 |
| 9 | 2 | False | 13:00:46.570 | 9 | 1 | False | 11:01:58.720 |
| 10 | 3 | False | 13:01:14.190 | 10 | 3 | False | 11:02:24.050 |

The EEG data signal obtained from each learner based on the results of filling in the RAPM is presented in figure 4. The EEG data signal for each learner, derived from the RAPM results, is illustrated in figure 5.

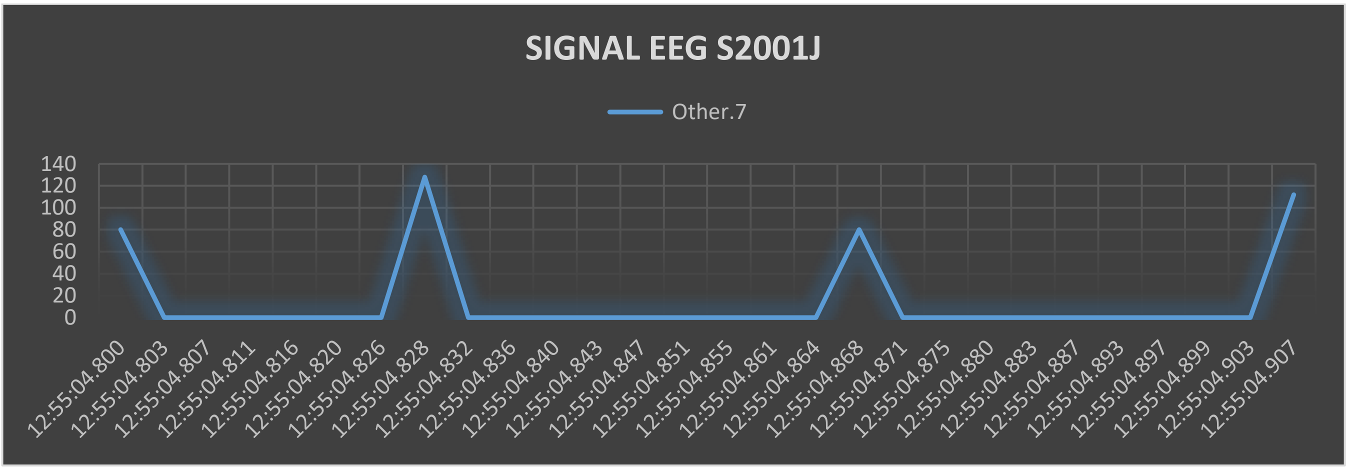


**Figure 4.** Signal EEG student 1

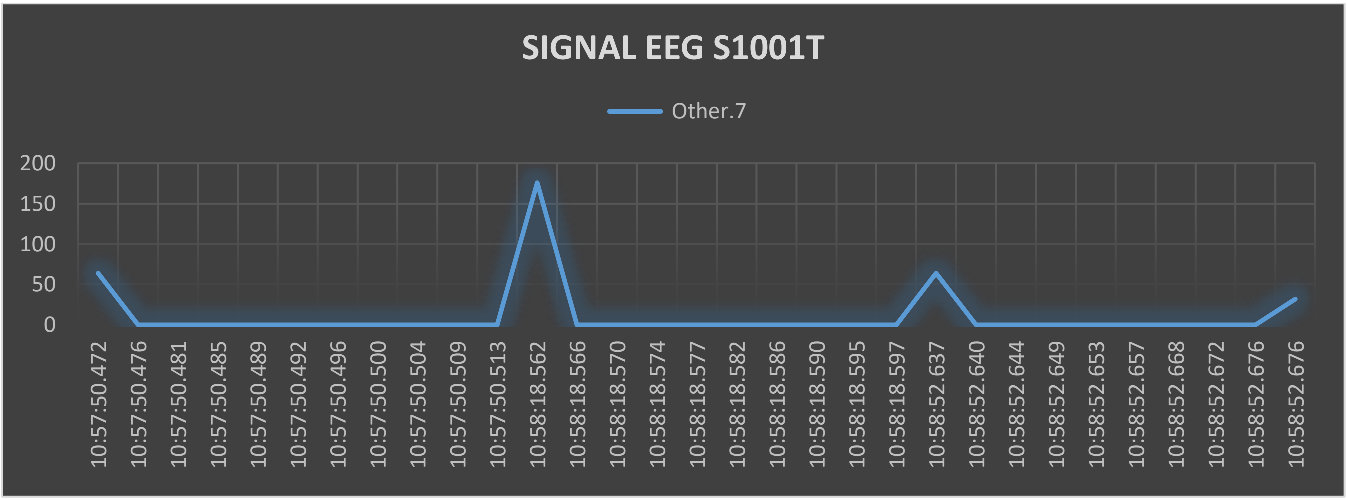


**Figure 5.** Signal EEG Student 2

The feature selection method used for EEG data with EXG Channels 0 to 7 is based on the collected data, where values above 100 are considered correct answers, and values below 80 are considered incorrect answers in this study. Below, table 5 presents information related to the EEG Learning Style dataset.

ISSN 2723-6471


**Table 5**. Dataset EEG Learning Style

| **ID** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** | **…** | **…** | **…** | **36** | **Label** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| S2001J | 4 | 1 | 4 | 5 | 3 | 7 | 3 | 1 | 1 | 3 | … | … | … | 8 | active |
| S2002K | 3 | 1 | 7 | 4 | 1 | 1 | 2 | 8 | 2 | 3 | … | … | … | 3 | active |
| S2003R | 5 | 1 | 0 | 4 | 3 | 1 | 6 | 1 | 8 | 4 | … | … | … | 0 | reflective |
| S2004Y | 5 | 1 | 7 | 7 | 7 | 7 | 8 | 1 | 7 | 8 | … | … | … | 8 | active |
| S2005F | 5 | 1 | 7 | 4 | 3 | 1 | 6 | 0 | 8 | 4 | … | … | … | 1 | reflective |
| S1001T | 5 | 2 | 7 | 7 | 1 | 1 | 6 | 1 | 8 | 8 | … | … | … | 4 | visual |
| S1002P | 5 | 2 | 7 | 0 | 7 | 3 | 6 | 1 | 8 | 3 | … | … | … | 1 | global |
| S1003R | 4 | 1 | 4 | 5 | 3 | 7 | 3 | 1 | 1 | 3 | … | … | … | 8 | active |
| …. | …. | …. | …. | …. | …. | …. | …. | …. | …. | …. | … | … | … | …. | active |
| …. | …. | …. | …. | …. | …. | …. | …. | …. | …. | …. | … | … | … | …. | reflective |
| …. | …. | …. | …. | …. | …. | …. | …. | …. | …. | …. | … | … | … | …. | active |
| …. | …. | …. | …. | …. | …. | …. | …. | …. | …. | …. | … | … | … | …. | reflective |
| S1103K | 4 | 1 | 8 | 5 | 3 | 7 | 3 | 1 | 1 | 3 | … | … | … | 8 | visual |

Table 6 below shows the mapping of Learning Styles with EEG. In table 6, the check mark represents the EEG signal recorded when the learner provides an answer to the Raven's Advanced Progressive Matrices (RAPM). Based on the mapping between the learner's responses and the corresponding EEG signals, Table 6 identifies the learner's learning style.

**Table 6.** Mapping EEG with Learning Style

| **Learning Style** | **EEG** | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 15 | 16 | 18 | 19 | 23 | 25 | 35 |
| Global | | | | √ | | √ | | | | | | | √ | | | √ | | | |
| Active | | √ | | | | | | | | | | | | | √ | | | √ | |
| Reflective | √ | √ | | √ | √ | √ | √ | | √ | √ | √ | | | √ | | | | | |
| Visual | √ | | √ | | | | | | | | √ | √ | | | | | √ | | √ |

In the context of EEG data collected from EXG Channels 0–7, model evaluation can be performed using several key metrics. Accuracy measures the overall performance of the model, while precision and recall evaluate the trade-off between correct predictions and errors. The F1-score balances precision and recall to provide a single comprehensive performance metric. Additionally, the confusion matrix helps analyze classification errors and misclassifications, offering insights into model weaknesses. Lastly, the AUC-ROC assesses the model's ability to differentiate between learning styles when employing probabilistic classification, ensuring a robust evaluation of predictive performance.

## 4.2. Accuracy

Used as an initial metric to assess overall model performance. Defined as:

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \tag{1}$$

## 4.3. Precision and Recall

Precision measures the proportion of correctly classified positive samples out of all predicted positive samples:

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \tag{2}$$

 ISSN 2723-6471 

Recall quantifies the ability of the model to correctly identify actual positives:

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FP}} \tag{3}$$

These metrics help analyze the trade-off between correct predictions and misclassification errors.

## 4.4. F1-Score

Used to balance precision and recall, especially in cases of class imbalance:

$$\text{F1} - \text{Score} = 2 \times \frac{\text{Precision+Recall}}{\text{Precision+Recall}} \tag{4}$$

## 4.5. Confusion Matrix

Provides a detailed breakdown of model predictions, allowing for better insight into classification errors. A sample confusion matrix is presented table 7 below:

**Table 7.** Confusion Matrix

| | Predicted Positive | Predicted Negative |
|---|---|---|
| Actual Positive | TP | FN |
| Actual Negative | FP | TN |

## 4.6. AUC-ROC Curve

Applied when the model is probabilistic or based on thresholding. Helps in selecting the optimal decision threshold by analyzing the trade-off between sensitivity and specificity. Table 8 below presents a comparison of the results with previous research.

**Table 8.** Research Results with Previous

| Method Propose | Data Source | Precision | Accuracy |
|---|---|---|---|
| CNN | EEG | 69.2% | 71.2% |
| Linear Regression (propose) | EEG | 89.4% | 96.4% |
| KNN (propose) | EEG | 75.5 % | 89.9% |

The proposed model for detecting learning styles using EEG data and machine learning algorithms demonstrated significant improvements in accuracy compared to previous studies. The Linear Regression (LR)-based model achieved an accuracy of 96.4%, while the K-Nearest Neighbors (KNN)-based model attained 89.9%. These results surpass the accuracy of 71.2% reported in prior research utilizing Convolutional Neural Networks (CNNs) for EEG-based learning style detection.

The enhanced performance of the LR model indicates its effectiveness in capturing linear relationships within the EEG data, a capability that may have been underutilized in CNN-based approaches. This suggests that simpler, well-tuned algorithms like LR may outperform more complex models when the dataset exhibits predominantly linear characteristics. Meanwhile, KNN, despite achieving lower accuracy than LR, also outperformed CNN-based models from prior research, further underscoring the importance of algorithm selection and preprocessing techniques.

The substantial improvement in accuracy highlights the potential of feature engineering and preprocessing techniques applied in this study. Unlike CNNs, which often require large datasets and intricate hyperparameter tuning to generalize effectively, LR and KNN benefited from carefully selected features and noise reduction, enabling them to extract meaningful patterns from limited EEG data.

Optimizing CNNs for EEG requires careful feature engineering, data augmentation, and architecture adjustments, such as hybrid models combining CNN with Long Short-Term Memory (LSTM) networks to better capture temporal dependencies. While CNNs hold potential in EEG analysis, their effectiveness depends on dataset characteristics, preprocessing strategies, and appropriate model selection tailored to the specific EEG application.

ISSN 2723-6471


Previous research employing CNNs may have faced challenges such as overfitting or inadequate representation of the EEG signal's essential characteristics. CNNs are typically designed for hierarchical feature extraction, which may not align with the relatively simple patterns in EEG data related to learning styles. In contrast, LR's ability to identify global relationships and KNN's instance-based learning approach allowed for better adaptation to the dataset's structure.

The findings of this study suggest that EEG signals contain distinct, linearly separable features that correspond to learning styles. By achieving an accuracy of 96.4%, the LR model demonstrates the feasibility of using simpler algorithms to outperform more computationally intensive methods like CNNs in this domain. This aligns with the notion that algorithm complexity should match the nature and size of the dataset to maximize performance.

## 5. Conclusion

This study successfully developed a model for detecting learning styles based on the Felder-Silverman model using EEG data and two machine learning algorithms LR and KNN. The results demonstrated that the LR-based model achieved a remarkable accuracy of 96.4%, while the KNN-based model reached 89.9%, significantly outperforming the accuracy of 71.2% reported in previous research using CNNs.

The findings highlight the advantages of employing simpler and well-tuned algorithms like LR and KNN for EEG-based learning style detection, particularly when the dataset exhibits linear characteristics. Careful feature engineering and preprocessing were critical to achieving these superior results. In contrast to the CNN approach, which relies on automated feature extraction, this study emphasized domain-specific features that proved more effective in capturing patterns related to learning styles.

The proposed models not only enhance accuracy but also offer practical advantages, such as lower computational complexity, making them suitable for real-time applications. These results demonstrate the feasibility of utilizing EEG data for accurate and efficient learning style detection, paving the way for adaptive learning systems and personalized educational strategies.

Future research should focus on expanding datasets, integrating advanced hybrid models, and exploring multimodal data to further improve the robustness and applicability of EEG-based learning style detection systems. This work provides a solid foundation for advancing personalized education through the innovative use of machine learning and physiological data. EEG devices have various types of calibrations that are required to ensure accuracy and consistency in measuring brain signals. These calibrations are important because they can affect the quality of the data obtained

## 6. Declarations

### 6.1. Author Contributions

Conceptualization: M.S.H., R.R.I., D.A.D., A.W.; Methodology: M.S.H., T.B.K; Software: M.S.H., T.B.K.; Validation: M.S.H., R.R.I., and A.W.; Formal Analysis: M.S.H., R.R.I., M.L.Y and A.W.; Investigation: M.S.H.; Resources: R.R.I.; Data Curation: R.R.I.; Writing Original Draft Preparation: M.S.H., R.R.I., and A.W.; Writing Review and Editing: R.R.I., M.S.H., and A.W.; Visualization: M.S.H. All authors have read and agreed to the published version of the manuscript.

### 6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

### 6.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

### 6.4. Institutional Review Board Statement

Not applicable.

### 6.5. Informed Consent Statement

Not applicable.

## 6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

**References**

[1] R. Felder and L. Silverman, "Learning and teaching styles in engineering education," *Engineering education*, vol. 78, no. June, pp. 674–681, 1988, doi: 10.1109/FIE.2008.4720326.

[2] D. A. Kolb, Experiential Learning: Experience as The Source of Learning and Development. Vol 1984, No January, pp. 21-38, doi: 10.1016/B978-0-7506-7223-8.50017-4.

[3] E. Hall, and K. Ecclestone, "Learning styles and pedagogy in post-16 learning A systematic and critical review," *Learning and Skills Research Centre*, vol 2004 no January, pp 160-171 doi: 10.1016/S0022-5371(81)90483-7.

[4] N. A. Rashid, T. M. Nasir, S. Lias, N. Sulaiman, Z. H. Murat, and R. S. S. Abdul Kadir, "Learners' Learning Style classification related to IQ and Stress based on EEG," *Procedia Soc Behav Sci*, vol. 29, no. October 2015, pp. 1061–1070, 2011, doi: 10.1016/j.sbspro.2011.11.339.

[5] L. Duan et al., "Machine Learning Approaches for MDD Detection and Emotion Decoding Using EEG Signals," *Front Hum Neurosci*, vol. 14, no. September, pp. 1–10, 2020, doi: 10.3389/fnhum.2020.00284.

[6] D. Deenadayalan, A. Kangaiammal, and B. K. Poornima, "EEG Based learner's learning style and preference prediction for E-learning," *Proceedings of the International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud), I-SMAC* 2018, no. 14, pp. 316–320, 2018, doi: 10.1109/I-SMAC.2018.8653693.

[7] B. Zhang, C. Chai, Z. Yin, and Y. Shi, "Design and implementation of an eeg-based learning-style recognition mechanism," *Brain Sci*, vol. 11, no. 5, pp. 1-12, 2021, doi: 10.3390/brainsci11050613

[8] N. Bin Abdul Rashid, M. N. Bin Taib, Z. B. Zunairah, R. S. B. Ros Shilawani, S. Bin Lias, and N. Bin Sulaiman, "Summative EEG alpha classification relates learning style and openness," *IEEE Global Engineering Education Conference, EDUCON*, no. April, pp. 807–810, 2014, doi: 10.1109/EDUCON.2014.6826188.

[9] R. M. Felder and R. Brent, "Understanding student differences," *Journal of Engineering Education*, vol. 94, no. 1, pp. 57–72, 2005, doi: 10.1002/j.2168-9830.2005.tb00829.x.

[10] S. Graf, "Adaptivity in Learning Management Systems Focussing on Learning Styles by," *Vienna University of Technology*, Vol 2007, no September, pp 235-239, 2007.

[11] M. Raleiras, A. H. Nabizadeh, and F. A. Costa, Automatic learning styles prediction: a survey of the State-of-the-Art (2006–2021), vol. 9, no. 4. *Springer Berlin Heidelberg*, 2022. doi: 10.1007/s40692-021-00215-7.

[12] R. Felder and J. Spurlin, "Applications, Reliability and Validity of the Index of Learning Styles," *International Journal of Continuing Engineering Education and Life-Long Learning*, vol 21. no 1, pp 103-112, 2005.

[13] T. A. Litzinger, S. H. Lee, J. C. Wise, and R. M. Felder, "A psychometric study of the index of learning styles©," *Journal of Engineering Education*, vol. 96, no. 4, pp. 309–319, 2007, doi: 10.1002/j.2168-9830.2007.tb00941.x

[14] S. Pagano, L. Lombardi, and V. Mazza, "Brain dynamics of attention and working memory engagement in subitizing," *Brain Res*, vol. 1543, no. 1, pp. 244–252, 2014, doi: 10.1016/j.brainres.2013.11.025.

[15] M. A. Ramírez-Moreno et al., "Eeg-based tool for prediction of university students' cognitive performance in the classroom," *Brain Sci*, vol. 11, no. 6, 2021, doi: 10.3390/brainsci11060698.

[16] N. A. Rashid, M. N. Taib, S. Lias, and N. Sulaiman, "Implementation of cluster analysis for learning style classification using brain asymmetry," Proceedings - 2011 IEEE 7th International Colloquium on Signal Processing and Its Applications, CSPA 2011, no. March, pp. 310–313, 2011, doi: 10.1109/CSPA.2011.5759893.

[17] B. Zhang, Y. Shi, L. Hou, Z. Yin, and C. Chai, "Tsmg: A deep learning framework for recognizing human learning style using eeg signals," *Brain Sci*, vol. 11, no. 11, 2021, doi: 10.3390/brainsci11111397.

[18] E. R. Supriyanto, R. Isnanto, and S. H. Purnomo, "Developing Chicken Health Classification Model Using a Convolutional Neural Network and Support Vector Machine (CNN-SVM) Approach," *Ingenierie des Systemes d'Information*, vol. 29, no. 6, pp. 2525–2532, Dec. 2024, doi: 10.18280/isi.290637

[19] C. Babiloni et al., "Alpha, beta and gamma electrocorticographic rhythms in somatosensory, motor, premotor and prefrontal cortical areas differ in movement execution and observation in humans," *Clinical Neurophysiology*, vol. 127, no. 1, pp. 641–654, 2016, doi: 10.1016/j.clinph.2015.04.068.

[20] R. Yuvaraj et al., “A Machine Learning Framework for Classroom EEG Recording Classification : Unveiling Learning-Style Patterns,” *Algorithms*, vol. 17, no. 11, pp. 1–19, 2024.

[21] S. Gupta, P. Kumar, and R. Tekchandani, “A machine learning-based decision support system for temporal human cognitive state estimation during online education using wearable physiological monitoring devices,” *Decision Analytics Journal*, vol. 8, no. April, pp. 1-16, 2023, doi: 10.1016/j.dajour.2023.100280.

[22] E. Başar, C. Başar-Eroğlu, B. Güntekin, and G. G. Yener, “Brain’s alpha, beta, gamma, delta, and theta oscillations in neuropsychiatric diseases: Proposal for biomarker strategies,” *Suppl Clin Neurophysiol*, vol. 62, no. 1, pp. 19–54, 2013, doi: 10.1016/B978-0-7020-5307-8.00002-8

[23] E. Başar and B. Güntekin, “Review of delta, theta, alpha, beta, and gamma response oscillations in neuropsychiatric disorders,” *Suppl Clin Neurophysiol*, vol. 62, no. 1, pp. 303–341, 2013, doi: 10.1016/B978-0-7020-5307-8.00019-3