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Recommendation Model for Learning Material Using the Felder Silverman Learning Style Approach

M. S. Hasibuan [1*], R. Z. Abdul Aziz [1], Deshinta Arrova Dewi [2], Tri Basuki Kurniawan [3], Nasywa Aliyah Syafira [4]

[1] *Faculty Computer Science, Institute Informatics and Business Darmajaya, Bandar Lampung, 35136, Indonesia.*

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

[3] *Faculty of Technology and Information Science, University Kebangsaan Malaysia, Malaysia.*

[4] *Faculty of Education, Yogyakarta State University, Yogyakarta, Indonesia.*

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Abstract

The biggest obstacle that students have when participating in a virtual learning environment (e-learning) is discovering a platform that has functionalities that can be customized to fit their needs. This is usually accomplished in several ways using educational resources such as learning materials and virtual classroom design elements. Our research has tried to meet this demand by suggesting an extra element in the virtual classroom design, i.e., classifying the students' learning styles through machine-learning techniques based on information gathered from questionnaires. This feature allows teachers or instructors to modify their lesson plans to better suit the learning preferences of their students. Additionally, this feature aids in the creation of a learning path that serves as a guide for students as they choose their course materials. In this study, we have selected the Felder-Silverman Learning Style Model (FSLSM) in the questionnaire design, which focuses on identifying the students' learning styles. After that, we employ several machine learning algorithms to create a prediction model for the students' learning styles. The algorithms include Decision Tree, Support Vector Machines, K-Nearest Neighbors, Naïve Bayes, Linear Discriminant Analysis, Random Forest, and Logistic Regression. The best prediction model from this exercise contributes to the recommendation model that was created using a collaborative filtering algorithm. We have carried out a pre-test and post-test method to evaluate our suggestions. There were 138 learners who were following a learning path and participated in this study. The findings of the pretest and post-test indicated a notable increase in students' motivation to study. This is confirmed by the fact that learners' satisfaction with online learning climbed to 87% when the learning style was considered, from 60% when it wasn't.

Keywords: Education Quality; Education Environment; Learning Style; Recommendation Model; Personalization.

1. Introduction

The field of education is a prime example of how quickly technological improvements are developing. Due to technological advancements, learning procedures have greatly changed. Learning can now happen virtually, using information technology, especially the Internet, as well as in traditional classroom settings. The phrase "anywhere, anytime, anyplace" refers to a form of education that can take place anywhere, at any time, and thanks to e-learning [1,

* Corresponding author: msaid@darmajaya.ac.id

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2]. The capacity to enable learning without the limitations of in-person attendance and set schedules is one of the main characteristics of online learning. However, e-learning has drawbacks for teachers as well as students. As fewer interactions occur between teachers and students, learners believe that maintaining a high level of motivation is crucial [3–5].

To improve student motivation in e-learning, instructors must establish e-learning methodologies. E-learning platforms should be able to extract learners' personalization characteristics at the same time, from a technological perspective. A type of personalization called learning style has been the focus of previous studies [6–9]. According to Keefe [10], learning style is characterized by cognitive, affective, and psychological traits that are utilized during the learning experience. Learning styles are unique and vary from person to person, according to Felder Silverman [11–13]. Students may experience discomfort and lose interest during the learning process if teachers do not consider their unique learning styles [14]. This could cause students to lag in their studies.

Since learning styles have a big impact on academic achievement, teachers must take them into account when designing their lesson plans. To guarantee effective teaching and learning programs, several studies highlight the importance of determining learners' learning styles [3]. Kolb's learning styles [15, 16], Honey and Mumford's styles [17], Myers and Briggs' types [18, 19], the VARK model [20], and the Felder Silverman Learning Style Model (FSLSM) [21, 22] are only a few of the learning styles that have been found. Two approaches can be used to identify learning styles: the traditional way, which involves employing questionnaires, and the automated approach, which is based on interactions between the learner and the system [12, 19]. Following the process of identifying their learning type, students frequently need tailored recommendations for educational resources and settings.

Based on identified learning styles and course levels, prior research has suggested instructional materials [20]. Recommendations were given by Imran et al. [23] in light of prior training materials and learning style similarities. By using a search, selection, rating, and suggestion process, Alfredo provided recommendations [24]. Based on the findings of a questionnaire used to predict learning styles, this study offers suggestions. A pre-test and post-test were conducted in order to verify the recommendations' outcomes. When posttest scores exceed pretest results, it indicates a strong level of learner motivation. The study also incorporates a learning path to help determine learners' preparedness to participate in the learning process [25–27]. Given that every instructional material has unique cognitive, emotional, and psychomotor effects, the learning path is the first step toward quantifying learning styles [28–30].

The aforementioned literature has made extensive reference to the value of learning styles in supporting students' academic endeavors. As a result, our research has recommended that learning styles be taken into account in educational settings, particularly in online or virtual learning environments.

2. Related Works

Research related to learning style detection has been conducted by Rasheed, who employed machine learning classification algorithms [31]. Rasheed's study involved 498 learner respondents and utilized methods like Decision Tree, Support Vector Machines, K-Nearest Neighbors, Naïve Bayes, Linear Discriminant Analysis, Random Forest, and Logistic Regression for learning style detection. Cross-validation scores were computed for four dimensions. Notably, the largest input dimension was achieved by Random Forest, Logistic Regression, and Linear Discriminant Analysis at 79%. The highest processing dimension was SVM, with 83% accuracy. The understanding dimension achieved a high accuracy of 83% using SVM, while the perception dimension utilized perception and achieved 91% accuracy. However, no recommendations were provided to learners based on the detection and validation results of their learning styles.

Another study focused on constructing learner profiles using the FSLSM model through clustering with the K-Means algorithm [32]. This study mapped learning objects and created learner profiles, then applied the K-Means algorithm for clustering. The results showed an accuracy of 78.83%, precision of 79.9%, recall of 83.1%, and F1 score of 80.12%. J. Feldman's research detected Felder-Silverman learning styles using puzzle games and the Naïve Bayes method [33]. This study included 45 learners, achieving an accuracy of 85% in learning style detection.

In terms of instructional material recommendations, Khairil et al. Proposed recommendations based on the similarity and quality of instructional materials to enhance understanding and improve grades [34]. Content-based filtering and good learning average ratings were employed. Another approach utilized collaborative learning by Poorni, involving a fuzzy tree-structured learning activity model and a learner profile model that led to recommendation architectures for administrators, students, and instructors [35]. Chen's research proposed an adaptive recommendation approach based on online learning styles (AROLS) by adopting collaborative, association rule, and clustering techniques [36].

The methods employed in the above literature have highlighted their strategies which differ from our recommendations in this regard. Our research has proposed integrating the machine learning approach, recommender system, and learning style into the learning environment, whereas prior work has approached these three areas independently. More explanations are provided in the following sections of this paper.

3. Research Methodology

The research methodology employed in this study is depicted in the diagram below, delineating the sequential phases commencing with the acquisition of learner data. The gathering of data on learning styles is executed through the utilization of the ILS questionnaire based on the Felder-Silverman Learning Style. Once the data is procured, the subsequent stage involves data preprocessing. This preprocessing procedure guarantees the data's preparedness for utilization in machine learning processes. The outcomes of the processing, employing techniques like K-Nearest Neighbors (KNN), Naïve Bayes, Decision Tree, Random Forest, and Neural Network, subsequently furnish recommendations. Elaborate clarifications pertaining to these stages are presented in Figure 1.

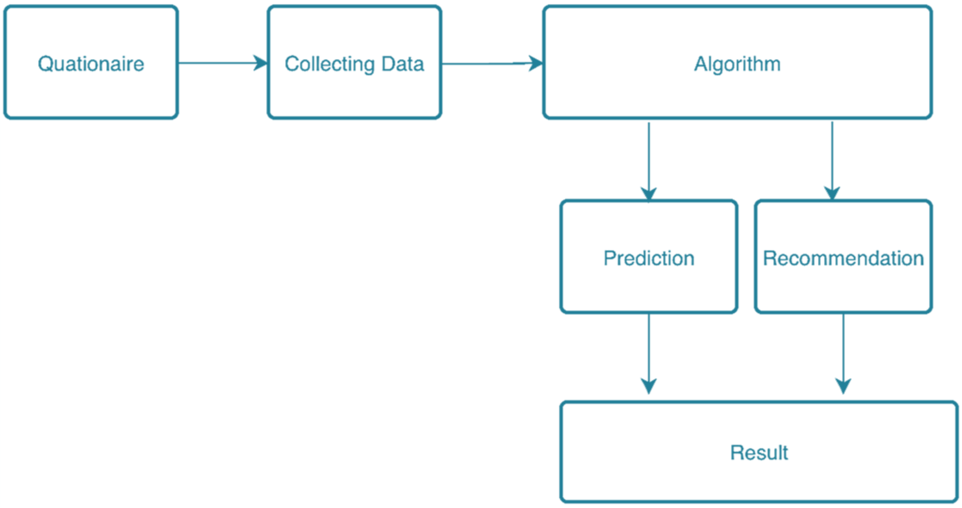

Figure 1. Research Methodology

3.1. Questionnaire

The questionnaire method involves data collection by presenting a set of written questions or statements related to the Felder-Silverman learning style to respondents for their responses.

3.2. Data Collection

The data obtained from the questionnaire results in the subsequent verification of initial data completeness. This step is crucial, as not all the data from the raw dataset will be utilized. Consequently, several attributes are identified for utilization. These attributes include: Name, Student ID, Gender, Class, Major, Course, Grade, Perception, Input, Understanding, Learning Style.

3.3. Algorithm Prediction

The next stage involves processing the questionnaire data using Algorithms such as Naïve Bayes [37], SVM [38, 39], Decision Tree [40], K-NN [41], Random Forest, and Neural Network. The processing yields predicted values from the detection process.

Naïve Bayes Algorithm

Naïve Bayes is a supervised learning algorithm based on the Bayes theorem and is used for classification problems by following a probabilistic approach. Naïve Bayes is selected due to its requirement for a relatively smaller dataset for processing. The following equation represents the Naïve Bayes algorithm.

$$P(H|X) = \frac{P(X|H).P(H)}{P(X)} \tag{1}$$

Where:

X: Data with an unknown class;

H: Hypothesis that the data belongs to a specific class;

P(H|X): Probability of hypothesis H given condition X (posterior probability);

P(H): Probability of hypothesis H (prior probability);

P(X|H): Probability of X given the condition of hypothesis H.

Algorithm Decision Tree

The Decision Tree algorithm is one of the methods that is relatively easy to interpret by humans. A decision tree is a prediction model that employs a tree-like or hierarchical structure. The concept behind a decision tree is to transform data into a decision tree and decision rules (see Figure 2).

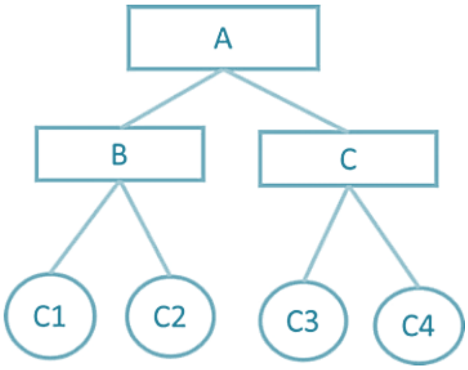

Figure 2. Classification model using decision tree

K-Nearest Neighbor (K-NN)

K-NN is a classification method that is very simple in classifying an image based on its nearest neighbors. Here is the equation for K-NN.

$$D(x, y) = \sqrt{\sum_{k-1}^{n}(x_k - y_k)^2} \tag{2}$$

Random Forest

Random Forest extends the Decision Tree approach by employing multiple Decision Trees, each trained with individual samples. In this ensemble, attributes are divided within the chosen tree across subsets of attributes selected at random.

Neural Network

A Neural Network is a computational model inspired by the structure and function of neural networks in the human brain [42–45]. This machine learning algorithm can process inputs and identify complex and abstract patterns within the data. Neural networks consist of artificial neurons connected in layers, where each neuron performs mathematical operations on its inputs and sends its output to neurons in the next layer. Through the learning process, the weights or parameters within the neural network are adjusted in such a way that the network can learn and recognize patterns within the data. Neural networks have been utilized in various fields, such as image recognition, natural language processing, and prediction.

3.4. Algorithm Recommendation

Content-Base Filtering (CBF)

This algorithm operates using items and users. In this study, items refer to learning elements such as learning methods and instructional materials, while users represent learners. The acquisition of learning environment values is generated from the responses to FSLSM learning style questions.

Collaborative Filtering (CF)

This recommendation algorithm functions by assigning ratings to instructional materials previously accessed by learners. The provision of recommendations is based on these instructional materials and is accompanied by examples and their implementations.

Hybrid Filtering

This algorithm is a combination of both Content-Based Filtering (CBF) and Collaborative Filtering (CF), typically utilizing if-then statements to generate recommendations.

Result

In an effort to measure the success of this research, the assessment includes measuring the outcomes of pre-tests and post-tests, as well as learner satisfaction with personalization. The calculation of the values obtained by learners is conducted using the following equation.

$$\text{Result} = (\sum postestscore - \sum pretestscore) \quad (3)$$

4. Result and Discussion

4.1. Questionnaire and Data Collection

The questionnaire utilized is the FSLSM questionnaire, consisting of 44 questions. The questions were presented to 138 learners through an online form. The outcomes of this questionnaire are as follows (see Table 1):

Table 1. The Result of Questionnaires

No.	ID	Processing	Perception	Input	Understand
1	20010001	Active	Intuitive	Visual	Sequential
2	20010002	Active	Intuitive	Visual	Sequential
3	20010003	Active	Intuitive	Visual	Sequential
4	20010004	Active	Intuitive	Visual	Sequential
5	20010005	Reflective	Sensing	Verbal	Global
6	20010006	Active	Intuitive	Visual	Sequential
7	20010007	Active	Intuitive	Visual	Sequential
8	20010008	Active	Intuitive	Visual	Sequential
9	20010009	Active	Intuitive	Visual	Sequential
10	20010010	Reflective	Sensing	Verbal	Global
…	……..	……..	……..	……..	……..
414	20020068	Reflective	Sensing	Verbal	Sequential

Based on the results of the above questionnaire, information about learning style preferences was obtained. There are four groups of learning styles with their corresponding activities: Processing, which includes active and reflective; Perception, consisting of Sensing and Intuitive; Input, comprising Visual and Verbal; and Understand, with Global and Sequential orientations. Quantitative outcomes from the questionnaire can be observed in Table 2.

Table 2. Value Conversion

NPM	Dimension								Learning Style
	Active	Reflective	Sensing	Intuitive	Visual	Verbal	Sequential	Global	
20010001	1	0	0	1	1	0	1	0	Active-Intuitive-Visual-Sequential
20010002	0	1	1	0	0	1	0	1	Reflective-Sensing-Verbal-Global
20010003	0	1	1	0	0	1	0	1	Reflective-Sensing-Verbal-Global
20010004	0	1	1	0	0	1	0	1	Reflective-Sensing-Verbal-Global
20010005	0	1	1	0	0	1	0	1	Reflective-Sensing-Verbal-Global
20010006	1	0	0	1	1	0	1	0	Active-Intuitive-Visual-Sequential
20010007	0	1	1	0	0	1	0	1	Reflective-Sensing-Verbal-Global
20010008	0	1	1	0	0	1	0	1	Reflective-Sensing-Verbal-Global
20010009	0	1	1	0	0	1	0	1	Reflective-Sensing-Verbal-Global
20010010	1	0	0	1	1	0	1	0	Active-Intuitive-Visual-Sequential
20010011	1	0	0	1	1	0	1	0	?

Based on the conversion results, a value of 0 is assigned to indicate no value, while a value of 1 signifies the possession of a learning style.

4.2. Processing the Dataset Using Algorithms

After the data is collected, pre-processing is conducted to ensure that the data can be processed in the subsequent stages. The total number of collected questionnaire responses is 414. As a result of data pre-processing, only 138 learner data sets are deemed usable. These data sets are then labeled according to the FSLSM learning style. The models involve the utilization of algorithms such as K-Nearest Neighbors (KNN), Naïve Bayes, Decision Tree, Random Forest, and Neural Network.

Figure 3 depicts the model of algorithm utilization using RapidMiner. In Figure 3, the questionnaire results data is uploaded, and nominal values are converted into numeric values. The "Multiply" function is used to process the K-Nearest Neighbors (K-NN), Naïve Bayes, Decision Tree, Random Forest, and Neural Network algorithms. Subsequently, the performance of all algorithms is evaluated, and the results can be observed in Table 3.

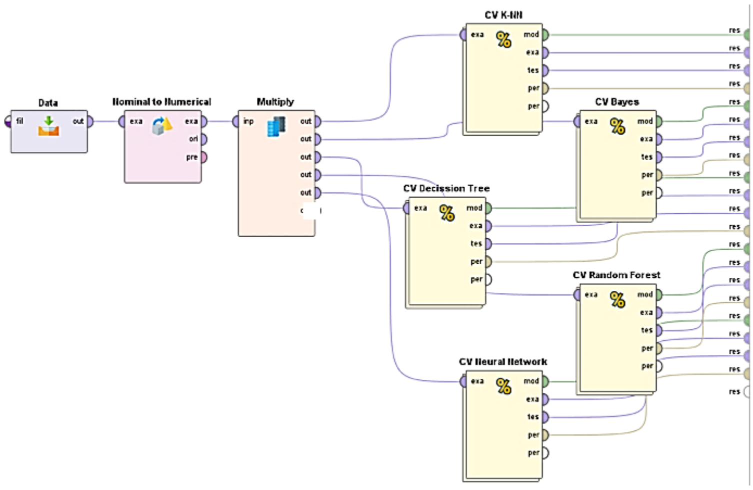

Figure 3. Illustrating the algorithm model using RapidMiner

4.3. Prediction and Recommendations

According to Table 3's results, the prediction level with the highest accuracy was made using a Neural Network and Naïve Bayes, then a KNN.

Table 3. Prediction Results

Fold	KNN	Naïve Bayes	Decision Tree	Random Forest	Neural Network
2	78.50%	97.34%	67.87%	67.87%	97.34%
3	81.88%	97.34%	67.87%	67.87%	97.34%
4	84.30%	97.34%	67.87%	67.87%	97.34%
5	86.73%	97.35%	67.88%	67.88%	97.35%
6	85.27%	97.34%	67.87%	67.87%	97.34%
7	86.74%	97.34%	67.88%	67.88%	97.34%
8	88.18%	97.35%	67.88%	67.88%	97.35%
9	86.96%	97.34%	67.87%	67.87%	97.34%
10	86.70%	97.35%	67.89%	67.89%	97.35%

Recommendations using Collaborative Filtering

Based on the recommendations of learning materials and learning styles, Table 4 represents the mapping of FSLSM learning styles with the recommended learning materials.

Table 4. Mapping of FSLSM with Learning Materials

	Text	Video	PPT	Exercise	Forum	Index
Act				√	√	√
Ref	√	√	√			
Sen		√	√			√
Int	√	√		√	√	
Vis		√				
Ver	√	√	√			
Seq	√					
Glo			√			√

Based on Table 4, the learner with NPM 20010001 has Active, Intuitive, Visual, and Sequential learning styles.

Table 5. Recommendation Results for NPM 20010001

	Text	*Video*	*PPT*	*Exercise*	*Forum*	*Index*
Act				√	√	√
Int	√	√		√	√	
Vis		√				
Seq	√					

Table 6. Recommendation Results for NPM 20010002. 20010003, 20010004, 20010005

	Text	*Video*	*PPT*	*Exercise*	*Forum*	*Index*
Ref	√	√	√			
Sen		√	√			√
Ver	√	√	√			
Glo			√			√

Table 7. Recommendation Results for NPM 20010006

	Text	*Video*	*PPT*	*Exercise*	*Forum*	*Index*
Act				√	√	√
Int	√	√		√	√	
Vis		√				
Seq	√					

The learner's suggestion model based on their learning style is shown in Tables 5, 6, and 7. For instance, it was suggested that the learner with ID 20010001 in Table 5 use a video, exercise, and forum as their learning tools. While students with IDs 20010002, 20010003, 20010004, and 20010005 are more likely to use PowerPoint and videos as their learning tools, regarding ID 20010006, it was advised that they do their study utilizing a video, an exercise, and a forum.

Learning Path

On the other hand, a learning path serves as a guide for the learning process, which can be observed in the Figure 4. Figure 4 represents the Learning Path of education, which contains information about the cognitive, affective, and psychomotor goals of the learning journey. Depicting this Learning Path is valuable in providing information regarding what preparations learners need to undertake to achieve their targets. Certainly, each learning topic has different achievements for each main topic and subtopic. For instance, in Data Mining education, learners are not immediately introduced to data processing practices. Instead, there's a foundation in concepts like data, databases, pre-processing, supervised learning, and unsupervised learning. The outcomes of these conceptual lessons contribute to cognitive understanding, while affective aspects pertain more to learners' skills in data manipulation.

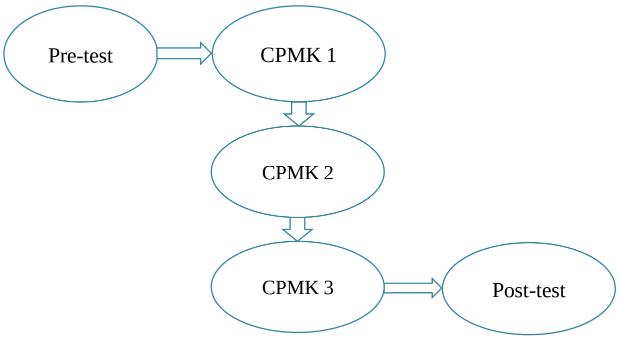

Figure 4. Pre-Test and Post-Test toward the Learning Path

The contrast between the pre-test and post-tests used in this study is explained in Figure 5. In comparison to the pre-test findings, the post-test results demonstrate a substantial improvement. Less than 80% is the highest level attained by the pre-test, whereas 100% is the highest level attained by the post-test. They also show how satisfied students are with how learning styles are incorporated into their studies.

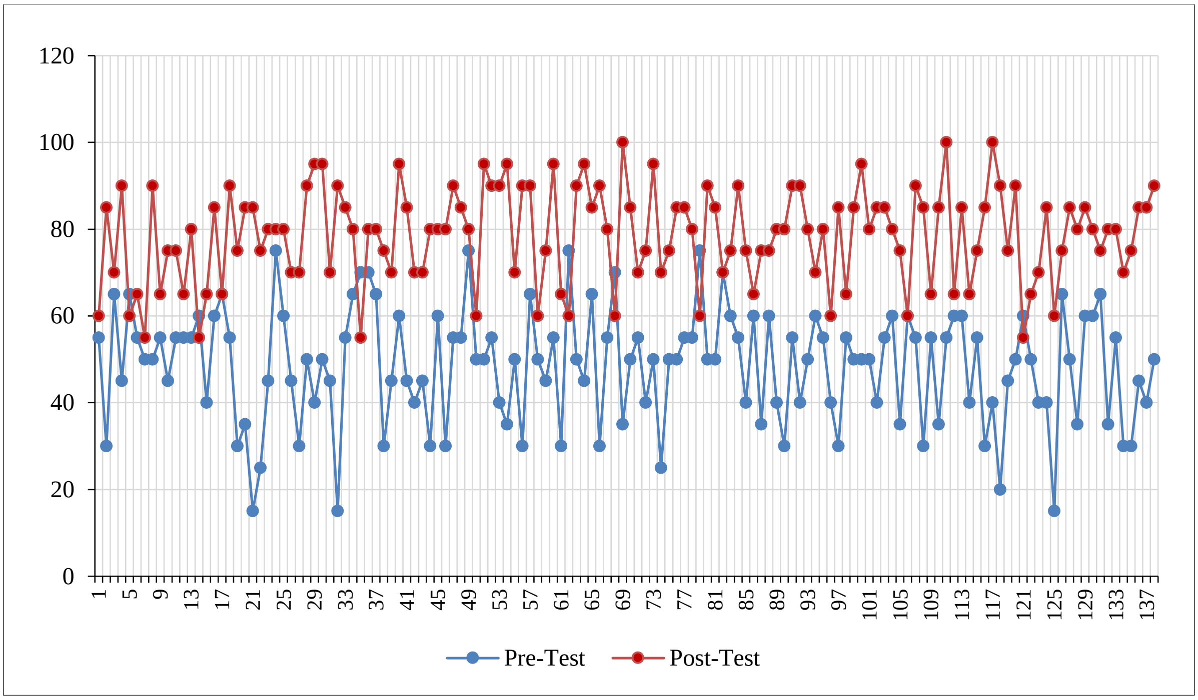

Figure 5. Compare Pre-test and Post-test

5. Conclusion

In terms of accuracy, the Naïve Bayes and Neural Network algorithms perform better than the K-Nearest Neighbors, Decision Tree, and Random Forest algorithms, according to experiments conducted with the Felder-Silverman learning style dataset, which included 138 learners. Learner performance is positively impacted by the application of the Felder-Silverman learning style detection approach through questionnaires and advice based on prediction results. The inclusion of a learning path can also greatly enhance student motivation, as this study has shown. It is noteworthy to acknowledge that the extent of the research surpasses the Felder-Silverman Learning Model alone.

6. Declarations

6.1. Author Contributions

Conceptualization, M.S.H.; methodology, M.S.H.; software, M.S.H.; validation, R.Z., D.A.D., and T.B.K.; formal analysis, M.S.H.; investigation, R.Z., D.A.D., and T.B.K.; resources, R.Z.; data curation, R.Z. and N.S.A.; writing—original draft preparation, M.S.H.; writing—review and editing, D.A.D.; visualization, D.A.D. and T.B.K.; supervision, T.B.K.; project administration, N.S.A.; funding acquisition, M.S.H. and D.A.D. 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

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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.

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