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Prediction of Various Computational Parameters using Naive Bayes and Felder and Silverman Methods

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Abstract: The increasing use of e-learning by students causes an LMS to consider student learning styles to provide comfortable content and improve the learning process. Learning style refers to the preferred way in which an individual learns in the best way. The traditional method for detecting learning styles (using questionnaires) has many limitations, namely the process of filling out the questionnaire is time consuming, and the results obtained are inaccurate because students are not always aware of their own learning preferences. So, in this study we use an approach to detect learning styles automatically, based on the Felder and Silverman learning style model (FSLSM) and use a machine learning algorithm. The proposed approach consists of two parts: The first part aims to extract the sequence of student activities from the log file, map with literature based then use an unsupervised algorithm (K-means) to group them into sixteen clusters according to FSLSM, and the second part uses a supervised algorithm (Naive Bayes) to predict learning styles for new activity sequences or new students. To take this approach, we use real datasets extracted from e-learning system log files. To evaluate performance, we used the confusion matrix. The more learning activities will increase the features and increase accuracy.

***Keywords**: LMS, Felder-Silverman learning style model, K-Means, Naïve Bayes*

1. Introduction

Learning Management System (LMS) provides various kinds of learning content for students as the main and supporting learning media. There is also customized LMS content for students based on their profile, with the ultimate goal of enhancing their learning process. Students process information and learn in different ways, and this can affect the teaching and learning process [1]. The learner profile is a representation of the learner's behavior when he interacts with the system, learner behavior can be captured from web logs using data mining techniques and then translated into a series of characteristics such as; skills, level of knowledge, preferences, and learning styles are considered as important factors that directly affect students' learning process. Learning style is the main characteristic of the learner and is taken into account in the process of personalizing learning, because it refers to the preferred way in which a learner perceives, treats and captures information. The major requirement of e-learning system is to provide a personalized interface with personalized contents which adapts to the learning styles of the learners. This is possible if the learning styles of the learner is known. [2].There are many learning style (LS) models in which each learner is categorized into a particular type of learning style based on the way students learn, many LS models have been proposed such as [3–5], and others. Felder Silverman Learning Style Model (FSLSM) is a popular learning style model that defines four dimensions (processing, perception, input and understanding) and eight categories of learners (active, reflective, sensing, intuitive, visual, verbal, sequential and global). In this study we used FSLSM for various reasons; first, because it is most widely used in adaptive e-learning systems and the most appropriate to implement it [6, 7], another reason is that FSLSM allows LS to be measured according to the Index of Learning Styles (ILS), ILS consists of four FSLSM dimensions, each with 11 questions. Using ILS, we can link LS to appropriate learning activities.

There are many methods to detect learning styles, the traditional method is using a questionnaire [8], this method is time consuming and the results are not accurate. So to obtain an efficient learning style, we must detect it automatically from log files containing student behavior using data mining techniques. In this study we use an approach that aims to detect student learning styles dynamically based on Felder and Silverman's learning style model [4] and use machine learning algorithms. In the first step of our approach, we have extracted the sequence of learning activities from log files, mapped them using literature based then we used an unsupervised algorithm to group them into sixteen clusters where each cluster corresponds to a combination of learning styles. In the second step, the clusters obtained from the first step have been considered as training datasets, then using a

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supervised algorithm on the datasets to predict the learning styles of the new activity sequences.

Many definitions appear in the literature on the term learning style. Laschinger and Boss [5] define learning style as the way in which individuals organize information and experiences, while Garity [9] defines it as the preferred way to learn and process information. Keefe and Thomson [10] describe learning styles as cognitive, effective, and psychological behaviors that serve as relatively stable indicators of how students perceive, interact with, and respond to the learning environment.

Learning style refers to the preferred way in which a student perceives, reacts, interacts with, and responds to the learning environment. Each student has his or her own preferred way of learning; there are some students who prefer to study in groups, discuss, some prefer to study alone; some prefer to learn by reading written explanations, others by looking at visual representations, pictures, diagrams, and charts. To ensure an efficient learning process for students; LMS must take into account the different learning styles of students.

A learning style model classifies students into a number of predetermined dimensions, where each dimension relates to the way they receive and process information. Many learning style models have been proposed in the literature, in this study we are based on the Felder and Silverman learning style model.

According to previous research [6, 7], FSLSM is the most widely used in adaptive e-learning systems and the most appropriate to implement. FSLSM presents four dimensions with two categories each, where each student has a dominant preference for one category in each dimension: processing (active/reflective), perception (sensing/intuitive), input (visual/verbal), understanding (sequential/ global).

Active learners (A) prefer to process information by interacting directly with learning materials, while reflective learners (R) prefer to think about learning materials. Active learners also tend to study in groups, while reflective learners prefer to work individually. Sensing learners (S) tend to use material that contains concrete facts and real-world applications, they are realistic and like to use demonstrated procedures and physical experiments. While intuitive (I) learners prefer to use material that contains abstract and theoretical information, they tend to understand the overall pattern of the global picture and then discover possibilities. Visual (Vi) learners prefer to see what they are learning using visual representations such as pictures, diagrams, and charts. While verbal learners (Ve) like information that is explained in words; both written and oral. Sequential (Seq) learners prefer to focus on details by following the course step by step in a linear fashion. In contrast, global learners (G) prefer to understand the big picture by organizing information holistically.

Many approaches have been proposed to automatically detect student learning styles based on machine learning techniques. These studies rely on various classifications. Feldman et al. [11] found that the Bayesian network classifier is one of the most widely adopted classifiers for inferring learning styles. Garcia et al. [12] used Bayesian Networks (BN) to detect student learning styles in a Web-based education system. To evaluate the appropriateness of their proposed approach, they compared the learning styles detected by their approach with the learning styles obtained by the learning style questionnaire index. Bunt and Conati [13] overcome this problem by building a BN that is able to detect the difficulties faced by students during the exploration process; then provide specific assessments to guide and enhance the learner's exploration of the available material.

Decision tree is a classification algorithm that is also often used in the field of automatic detection of learning styles. Kalhoro [14] proposes an approach to automatically detect student learning styles from student web logs using Data Mining techniques, and Decision Tree classifiers. Kolb's learning style theory was included to understand student learning styles on the web. Pantho and Tiantong [15] proposed an approach to classify students' VARK (Visual, Aural, Read/Write, Kinesthetic) learning styles using the Decision Tree C4.5 algorithm. Data on student learning styles were collected through questionnaires which were responded to by 1205 students. The collected data is then classified using the Decision Tree C4.5 algorithm.

Neural networks are also commonly used in the automatic detection of learning styles, Hmedna et al. [16] proposed an approach that uses neural networks to identify and track learner learning styles to ensure efficient resource recommendations. Their work is based on the Felder-Silverman dimension. Hmedna et al. [16] introduced an automated student modeling approach to identify learning styles in the learning management system according to FSLSM. They proposed the use of FCMs fuzzy cognitive maps as a tool to identify students' learning styles. FCM is a computational software which is a combination of fuzzy logic and neural networks.

Similarly with the previous algorithm; KNN is often used to detect learning styles automatically, Chang et al. [17] proposed a learning style classification mechanism to classify and then identify students' learning styles. The proposed mechanism improves the classification of k-nearest neighbors (k-NN) and combines them with a genetic algorithm (GA).

According to [18], has studied how learning styles affect student performance in e-learning systems. They studied the impact of using learning styles to build recommendations for students, teachers, and online course content. In the article [11], several research results on learning style detection are reviewed, analyzed, and summarized with a discussion of the limitations, engagements and challenges of research that can be considered as useful insights to find new methods and approaches in the field of style detection. study.

Research [18] uses the Naïve-Bayes Tree as a classification method to classify student learning styles according to FSLSM. As a first step, learning styles were detected using the Index of Learning Styles (ILS) questionnaire. This questionnaire was developed by Felder and Silverman. It consists of 44 questions to identify learning styles. However, it is too difficult to identify students' learning styles by relying solely on Felder and Silverman's questionnaire. In fact, additional factors must be taken into account to find the appropriate learning style such as online usage behavior and the type of learning object.

The author [17] presented a learning style classification technique to classify and identify students' learning styles. The students were classified according to three learning styles: dilatory students, temporary students and persistent students. This classification is based on the student's behavior and the time spent studying the object. The author combines genetic algorithms with improved K-NN to classify students according to their learning styles.

In [19], the author has proposed a method that combines the Artificial Neural Network technique based on Multi-Layer Perceptron to classify student data. The proposed method combines a set of behavioral characteristics taken from the learning sessions to increase the accuracy of learning style predictions. The classification step relies on classifying student data based on four categories (Active-Reflective and Sequential-Global) of students provided by FSLSM. As is known, all previous studies used a learning style model in their approach. Most of the proposed approaches use FSLSM dimensions and assume that there are 8 learning styles in which each corresponds to a dimension category. In fact, there are sixteen combinations of learning styles obtained by combining one category from each dimension.

2. Method

To identify student learning styles we have to use standard learning style models such as FSLSM, where the captured sequence can be labeled with a particular combination of learning styles using an unsupervised algorithm. To implement the unsupervised algorithm, the sequence of student activities that have been extracted from the log file, must be transformed to the input of the algorithm. The order of a student's learning activities is determined by the various learning activities carried out by students during a particular session. Each learning activity sequence contains the user's full name, event context, component, and event name that are accessed by students in a session.

In this study, not all learning activities are available. This is because this study uses a pure Moodle LMS that has not been modified. Therefore, a literature-based processing process needs to be carried out in this study. This process is carried out by analyzing the learning activities contained in the pure Moodle LMS, then analyzing the literature on Felder and Silverman's learning styles. Felder and Silverman stated learning styles in the form of combined values from existing dimensions. For each value in each dimension, a mapping of the corresponding learning activity is carried out.

The results of this dimension value mapping still have to be processed further. The aggregation process from the mapping results is carried out to get the learning activity vector for the appropriate combination of learning styles. This result is fed as the initial centroid in the clustering process. After detecting the sequence of student activities; our first goal was to classify them according to FSLSM by assigning a particular combination of learning styles to each sequence, and our second goal was to use those labeled sequences as training sets to predict the learning styles of the new sequences.

In the first step we have used a grouping algorithm, while in the second step we have used a classification algorithm. In our approach, we have used the following two algorithms:

a. K-means algorithm: to assign a label to each sequence of learning activities based on FSLSM.
b. Naïve Bayes classifier: to classify new student learning activities, or new sequences of existing student learning activities according to FSLSM. The following schematic describes our approach (Figure. 1).

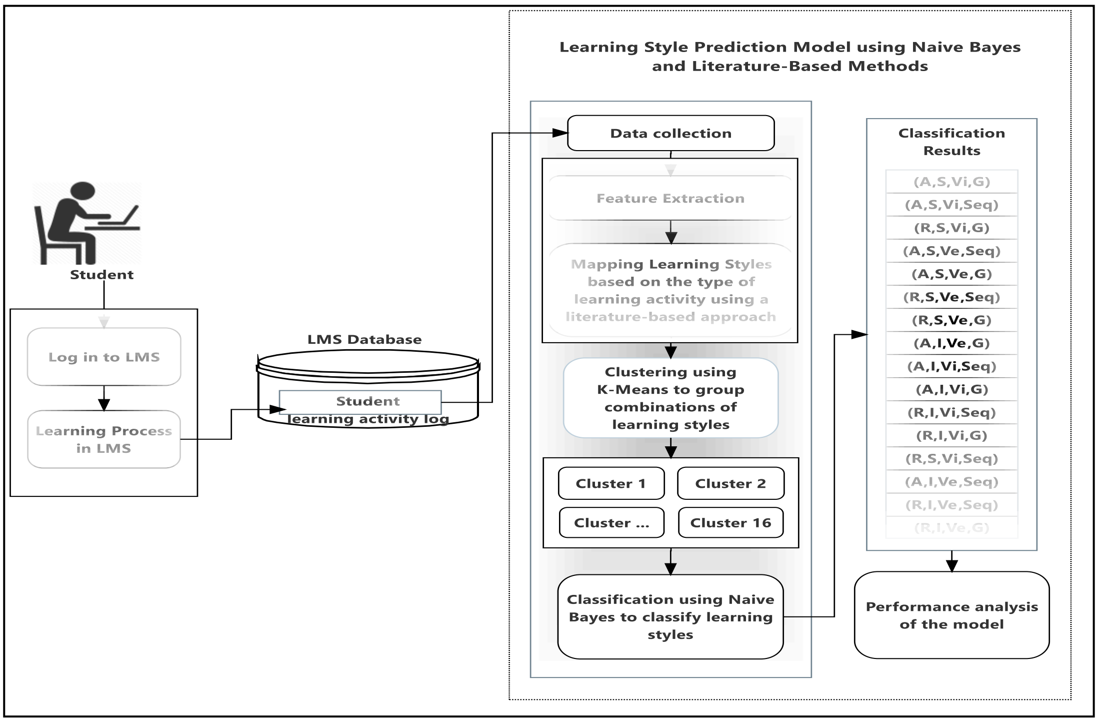


Fig. *1*. Our approach

The following subsections are structured as follows: first, we will show how to match each learning object with the appropriate combination of learning styles, then we will explain how clustering and classification algorithms are used in our approach.

A. Matching Learning Style Combination with Learning Activity

To match LSC with learning objects, we have to rely on LMS, in our work we are based on FSLSM for many reasons, one important reason is that FSLSM considers students' learning styles to change suddenly. and in a non-deterministic manner [6], therefore, our approach aims to dynamically update students' learning styles after each interaction with an adaptive e-learning system. According to previous research [7], FSLSM is the most widely used in adaptive e-learning systems and the most appropriate to be implemented. According to FSLSM there are four dimensions, where each dimension contains two opposite categories, and each learner prefers a certain category in each dimension. Thus, to identify the learning styles of students; we must determine the combinations composed by one category of each dimension.

B. Clustering

One of the contributions of this research is to match each learning activity with appropriate learning style preferences based on FSLSM to determine student learning styles. Because the sequence of students consists of learning activities carried out by students during the learning process, then to identify the learning style / learning style (LS) of each sequence of learning activities, it is necessary to determine the preference of the learning style that is referred to by each learning activity. Table 1 presents a mapping of learning activities on the dimensions of learning styles, as a reference, namely the results of Graf's research [20].

Table 1. Mapping of Learning Activities on the Dimensions of Learning Style

	***File PDF:* Course module viewed**	***URL Video:* Course module viewed**	***URL Example:* Course module viewed**	***Quiz (Exercise):* Quiz attempt submitted**	***Quiz (Exercise):* Quiz attempt viewed**	***Assessment):* Quiz attempt submitted**	***Quiz (Self Assessment):* Quiz attempt viewed**	***Forum:* Discussion viewed**	***Page Outline Global:* Course module viewed**	***Label Navigation:* Navigation attempt**
Active (A)	x			x	x	x	x	x		
Reflective (R)	x	x	x						x	

Sensing (S)			x	x	x	x	x			
Intuitive (I)	x	x								
Visual (Vi)		x	x							
Verbal (Ve)	x							x		
Sequential (Seq)										x
Global (G)									x	

According to FSLSM there are four dimensions, each dimension contains two opposite categories, and each student/student/learner prefers a certain category in each dimension. Thus, to identify student learning styles, must determine a combination consisting of one category from each dimension. The results in Table 1 have 8 data lines, the eight data lines are sourced from FSLSM dimensions, namely perception, input, processing, and understanding. As a result, 16 combinations were obtained:

Learning Styles Combinations (LSCs) = { (A,S,Vi,G), (A,S,Vi,Seq), (R,S,Vi,G), (A,S,Ve,Seq), (A,S,Ve,G), (R,S,Ve,Seq), (R,S,Ve,G), (A,I,Ve,G), (A,I,Vi,Seq), (A,I,Vi,G), (R,I,Vi,Seq), (R,I,Vi,G), (R,S,Vi,Seq), (A,I,Ve,Seq), (R,I,Ve,Seq), (R,I,Ve,G) }

Basically, each Learning Styles Combinations (LSC) reflects the preferred learning activity that students will always access during the learning process, so to identify the LSC for each student, one must first match the learning activity with the appropriate LSC. Based on the matching table presented in the previous subsection (Table 1.), Table 2 is obtained, where the mapped learning objects are considered as feature values of the K-means grouping algorithm.

Table 2 is obtained based on Table 1, namely the coordinates of each LSC vector obtained by aggregating the ones in Table 1, because each LSC is obtained by combining one Learning Style Preferences (LSP) from each dimension.

The clustering process is carried out by determining the k value of 16. The value of 16 is obtained based on the number of combinations of learning styles used in this study. By using the activity sequences that have been normalized as input and the learning style combination vector as the initial centroid.

One cluster generated in this clustering process represents a combination of learning styles. However, the clustering process itself cannot determine the combination of learning styles represented by a cluster. An additional process that must be carried out is to map the clusters that have been formed with a combination of learning styles.

The application of K-Means Clustering in this study was carried out with modifications. In the unmodified K-Means Clustering algorithm, the initial centroid is obtained by going through a randomization process. In this study, K-Means Clustering was carried out by giving a predetermined initial centroid value. This initial centroid value comes from the learning style combination vector. This learning style combination vector is the result of the literature processing process.

Table 2. Coordinates of Learning Style Combination Vector

	File PDF:* *Course module viewed	***URL Video:* *Course module viewed***	***URL Example:* *Course module viewed***	***Quiz (Exercise):* *Quiz attempt submitted***	***Quiz (Exercise):* *Quiz attempt viewed***	***Quiz (Self Assessment):* *Quiz attempt submitted***	***Quiz (Self Assessment):* *Quiz attempt viewed***	***Forum:* *Discussion viewed***	***Page Outline Global:* *Course module viewed***	***Label Navigation:* *Navigation attempt***
(A,S,Vi,G)	1	1	2	2	2	2	2	1	1	0
(A,S,Vi,Seq)	1	1	2	2	2	2	2	1	0	1
(R,S,Vi,G)	1	2	3	1	1	1	1	0	2	0
(A,S,Ve,Seq	2	0	1	2	2	2	2	2	0	1

)										
(A,S,Ve,G)	2	0	1	2	2	2	2	2	1	0
(R,S,Ve,Seq)	2	1	2	1	1	1	1	1	1	1
(R,S,Ve,G)	2	1	2	1	1	1	1	1	2	0
(A,I,Ve,G)	3	1	0	1	1	1	1	2	1	0
(A,I,Vi,Seq)	2	2	1	1	1	1	1	1	0	1
(A,I,Vi,G)	2	2	1	1	1	1	1	1	1	0
(R,I,Vi,Seq)	2	3	2	0	0	0	0	0	1	1
(R,I,Vi,G)	2	3	2	0	0	0	0	0	2	0
(R,S,Vi,Seq)	1	2	3	1	1	1	1	0	1	1
(A,I,Ve,Seq)	3	1	0	1	1	1	1	2	0	1
(R,I,Ve,Seq)	3	2	1	0	0	0	0	1	1	1
(R,I,Ve,G)	3	2	1	0	0	0	0	1	2	0

The modifications made to the K-Means Clustering algorithm were taken for 2 reasons. The first reason is that by using a fixed initial centroid, each clustering process is run with the same data, a fixed cluster and centroid will be generated. The second reason is that by using a known initial centroid, it will be easy to map clusters formed with a combination of FSLSM learning styles. If the K-Means Clustering algorithm in this study uses a random initial centroid, these two things are difficult to obtain.

Table 3. Mapping of Centroid Results against Initial Centroid Label

Centroid Results	**Initial centroid label**
1	A,S,Vi,G
2	A,S,Vi,Seq
3	A,S,Ve,G
4	A,S,Ve,Seq
5	A,I,Vi,G
6	A,I,Vi,Seq
7	A,I,Ve,G
8	A,I,Ve,Seq
9	R,S,Vi,G
10	R,S,Vi,Seq
11	R,S,Ve,G
12	R,S,Ve,Seq
13	R,I,Vi,G
14	R,I,Vi,Seq
15	R,I,Ve,G
16	R,I,Ve,Seq

Table 4. The number of students in each combination of learning styles

Combination of Learning Styles	Number of Students
(A,S,Vi,G)	16
(A,S,Vi,Seq)	2
(A,S,Ve,G)	23
(A,S,Ve,Seq)	8
(A,I,Vi,G)	3
(A,I,Vi,Seq)	12
(A,I,Ve,G)	2
(A,I,Ve,Seq)	1
(R,S,Vi,G)	22
(R,S,Vi,Seq)	29
(R,S,Ve,G)	32
(R,S,Ve,Seq)	13
(R,I,Vi,G)	16
(R,I,Vi,Seq)	6
(R,I,Ve,G)	16
(R,I,Ve,Seq)	4
	205

For each centroid generated in the K-Means Clustering process, there will be one cluster generated. In accordance with how K-Means Clustering works, the first initial centroid will be the first centroid generated by the clustering process. Likewise with the second centroid and so on. Based on these properties, label mapping can be done on the initial centroid with the clustered centroid results. The results of the mapping can be seen in Table 3.

Each centroid in the clustering results is also related to the resulting cluster. Every data that is input for K-Means Clustering will enter exactly 1 cluster. The results of this clustering are combined with the results in Table 3. From the results of this merger, each input data that states students will get a label in the form of a combination of learning styles. Table 4 shows the number of students in each combination of learning styles.

C. Classification

After applying the K-Means algorithm and labeling the sequences with Learning Style Combination (LSC), the labeled sequences are used as a training dataset to train the classification algorithm, and then use them to predict the LSC for the new sequences.

In this study, researchers have applied the Naive Bayes classifier for various reasons. First, because it is one of the most efficient machine learning algorithms, it learns quickly and predicts in the same way, and doesn't require a lot of storage. A very important characteristic of Naïve Bayes for this study is that this algorithm is a probabilistic classification method, therefore, in this approach, it is assumed that the learner LSC is not deterministic and not stationary because it can be changed during the learning process in an unexpected way, thus it can measure the LSC for a particular student after each iteration using a probabilistic method. Given a sequence Si defined with 10 attributes (A1, . . Aj , … , A10) with:

A1 : File PDF: Course module viewed

A2 : URL Video: Course module viewed

A3 : URL Example: Course module viewed

A4 : Quiz (Exercise): Quiz attempt submitted

A5 : Quiz (Exercise): Quiz attempt viewed

A6 : Quiz (Self Assessment): Quiz attempt submitted

A7 : Quiz (Self Assessment): Quiz attempt viewed

A8 : Forum: Discussion viewed

A9 : Page Outline Global: Course module viewed

A10 : Label Navigation: Navigation attempt

Each attribute Aj has two possible attribute values aj = {yes or no}, yes if the j[th] learning activity is in order, no if the j[th] learning activity is not in order. Given a set of labels that have been classified as C = {C1, C2, … , C16} with Ci corresponding to one of the sixteen LSCs.

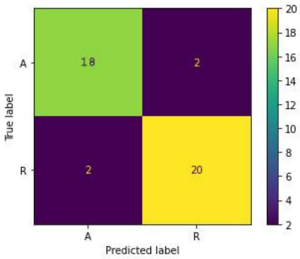
3. Results and Discussion

Performance Metrics for Classification Problems

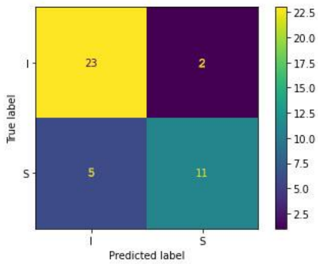
To evaluate the performance of the classifier used in this study, a confusion matrix was used. A confusion matrix is a special table layout that summarizes the number of true and false predictions in each class, and is used to calculate several validation metrics. Table 5 shows the results of the average evaluation using the confusion matrix on the four dimensions of the FLSM learning style for 5 trials.

Table 5. Average evaluation results using confusion matrix

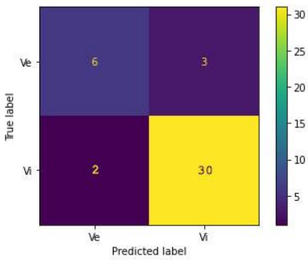
	Processing dimension		**Perception dimension**		**Input dimension**		**Understanding dimension**	
	A	**R**	**I**	**S**	**Ve**	**Vi**	**G**	**Seq**
accuracy	0.92		0.83		0.88		0.71	
precision	0.92	0.93	0.83	0.85	0.78	0.90	0.64	0.81
recall	0.91	0.93	0.92	0.71	0.64	0.95	0.84	0.59
f1-score	0.91	0.93	0.87	0.76	0.69	0.92	0.73	0.68



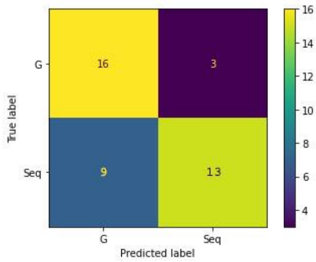
a. Processing dimension



b. Perception dimension



c. Input dimension



d. Understanding dimension

Fig. 2. Confusion Matrix for each dimension

Discussion

In this case the confusion matrix is not directly used to evaluate the predicted results of learning style combinations, but is used to evaluate per dimension of learning styles, because the support value (number of events) in the prediction results of learning styles is considered insufficient. Based on the available data, research results will always be obtained with low support for certain classes (combined learning styles). By doing a per-dimensional analysis, the results obtained have a more acceptable support value. So that the evaluation of learning styles is carried out per dimension, as well as to determine the level of evaluation of each category of the dimensions of the learning style.

Based on the average perdimensional evaluation results using the confusion matrix, it was found that the processing dimension has an accuracy of 92% which has 10 mappings with learning activities, the perception dimension has an accuracy of 83% which has 7 mappings with learning activities, the input dimension has an accuracy of 88%

which has 4 mappings. with learning activities, and the understanding dimension has an accuracy of 71% which only has 2 mappings with learning activities. Based on results, it can be analyzed if more learning activities will increase features and increase accuracy.

4. Conclusion

This study produces a model to predict learning styles in the Learning Management System (LMS) based on the existing learning activities in the Moodle LMS. The experiment was carried out using data from student activity logs for Data Structure, Software Engineering, and Information System Analysis and Design with students from different batches, a total of 205 students. The approach to detecting learning styles automatically consists of two main steps. The first aims to group (clustering) according to Felder and Silverman's learning style model, first to map learning activities from log files to FSLSM learning styles using a literature based approach to be used as input to the clustering algorithm. Then the sequence of students' learning activities are grouped according to Felder and Silverman's learning style model using the K-means clustering algorithm. In the second step, the labeled sequence obtained from the previous step is used as a training dataset to train using the Naive Bayes classification algorithm, then finally use it for testing. The learning style detection model that has been produced is used to personalize a course in the learning management system for each student, besides that learning styles can be directly predicted without students having to fill out the Learning Style Index (ILS) questionnaire repeatedly.

Further research can be carried out on a larger number of courses while still preparing in terms of content so that learning behavior patterns that are relevant to learning styles can be tracked properly. Further research can compare the accuracy results with data that already has a label from the questionnaire. Students need to be prepared and asked to fill out questionnaires from Felder and Silverman to be compared with literature-based methods. It is necessary to increase the amount of data so that the results obtained are better and not biased. From the model obtained, further research can develop an e-learning personalization system to accommodate learning content that is in accordance with the learner's learning style.

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