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ORIGINAL RESEARCH

STUDENT BEHAVIOUR ANALYSIS TO DETECT LEARNING STYLES USING DECISION TREE, NAÏVE BAYES, AND K-NEAREST NEIGHBOR METHOD IN MOODLE LEARNING MANAGEMENT SYSTEM

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Abstract

A learning management system (LMS) manages online learning and facilitates interaction in the teaching and learning processes. Teachers can use LMS to determine student activities or interactions with their courses. Everyone learns uniquely. It is necessary to understand their learning style to apply it in students' learning activities. One factor contributing to learning success is the use of an appropriate learning style, which allows the information received to be appropriately conveyed and clearly understood. As a result, we require a mechanism to identify learning styles. This study develops a learning style detection system based on learning behavior at the LMS of Christian Vocational School Petra Surabaya for the subject of Network System Administration using the Decision Tree, Naïve Bayes, and K-Nearest Neighbor. The results of the study showed that the Decision Tree method could better detect and predict learning styles, namely using the 80:20 train split test, which obtained an accuracy of 0.96 process time of 0.000998 seconds, while the K-Fold 10 Cross-Validation test obtained an accuracy of 0.98 and a processing time of 0.04033 seconds.

KEYWORDS:

Decision Tree, K-Nearest Neighbor, Learning Management System, Naïve Bayes, Student Learning Style

1 | INTRODUCTION

The COVID-19 pandemic, which ravaged the world, including Indonesia, had far-reaching ramifications in many aspects of life, including education. As a result, educational institutions are shifting away from traditional face-to-face learning and toward distance learning activities, acknowledging that learning and teaching must continue even when students are not in school. Finally, educational institutions have started to use online media for distance learning.

Learning management system (LMS) is an online learning management platform allowing students to access learning materials easily. Several LMS features represent the interaction between teachers and students. Teachers can use these services to help and motivate students to learn [1]. Many students, however their strengths and weaknesses. Because everyone understands materials differently, it is essential before applying them to process.

Learning style is a person's habit or characteristic in understanding learning material, which creates a comfortable and effective learning process. Learning styles are created from a person's habit of receiving learning materials processed using different methods, both in listening to the audio, watching videos, and reading texts. One of the factors supporting learning success is using an appropriate learning style so that the information received can be conveyed properly and clearly [2]. Several learning style models described by Feldman et al. [3] are using 4 dimensions:(1) Processing: Active/Reflective; (2) Perception: Sensitive/Intuitive; (3) Inputs: Visual/Verbal; (4) Understanding: Sequential/Global. FSLSM can define two different learning styles, and each dimension can produce one criterion. This model good System because learning style preferences are more specific. Thus, each learning style dimension can be modeled using student habits in using features in LMS while using it [4].

This study chooses three methods to identify learning styles. This study detected learning techniques based on students' behavior on the LMS. A questionary was employed, and several classification algorithms were used. The accuracy was calculated using a train split value of 80:20 and a k-fold value of 10 cross-validations.

2 | PREVIOUS RESEARCHES

There are several secondary studies, such as surveys and reviews related to student behavior analysis to detect learning styles. Those studies can be classified into two main groups. Some studies focused on classification methods [5–12]. Other studies focused on behavior modelling [13–15].

Ikawati et al. [5] discussed studies related to methods proposed in identifying student behavior based on Felder and Silverman concluded that the classification method using the Decision Tree method had a lower accuracy rate of 85.71% compared to the Gradient Boosted Tree method, which had an accuracy rate of 85.95%. Kolekar et al. [7] discussed studies related to the proposed Fuzzy C-Means Clustering method theory adaptation. The conclusion of the analysis are Active (0.77), Reflective (0.1) Sensing (0.2) inbuilt (0.35), Visual (0.75), Verbal (0.3) Sequential (0.8) universal (0.72).

Aissaoui et al. [8] discussed studies related to combining supervised and unsupervised algorithms. The higher the validation metrics, the better the classifiers. This study states that all the validation metrics: Accuracy, Recall (Sensitivity), Specificity, Precision (PPV), and NPV have high scores. This study says that the classifiers used in our approach have been carried out well. Rasheed and Wahid [9] discussed studies on the proposed classification algorithm and compared accuracy behavior studying various concepts. SVM of 75.55%, Decision Tree 45.55%, Logistic Regression 73.33%, Random Forest 73.33%, K-Nearest Neighbors 67.77%, Linear Discriminant 69.44%, and Naive Bayes 70.55%.

Additionally, Lwande et al. [6] discussed studies related to proposed research by combining the framework Systems and using Kappa statistics to show that inter-rater reliability results are quite appropriate. Score showing: active (0.26), reflective (0.74), sensing (0.69), intuitive (0.31), verbal (0.22), visual (0.78), sequential (0.15), global (0.85). Pasina et al. [10] discussed studies on clustering methods to classify grade-level engineering students into several groups. Index employed to end performance same of kinds. Bernard et al. [11] discussed studies related to proposing computational algorithm methods such as results study of Artificial Neural Network A/R 10, S/I 10, V/V 10, S/G 10; Genetic Algorithm A/R 10, S/I 32, V/V 27, S/G 10; Ant Colony System A/R 10, S/I 32, V/V 27, S/G 10; Particle Swarm Optimization System A/R 10, S/I 10, V/V 10, S/G 10. Finally, Crockett et al. [12] discussed studies related to the proposed fuzzy method approach to build a set of fuzzy prediction models combining variables for all dimensions of Felder Silverman's Learning Style model. The results using direct data show that the fuzzy model has improved the predictive accuracy of OSCAR-CITS across four learning style dimensions and facilitated the discovery of some interesting relationships among learning style behavioral variables.

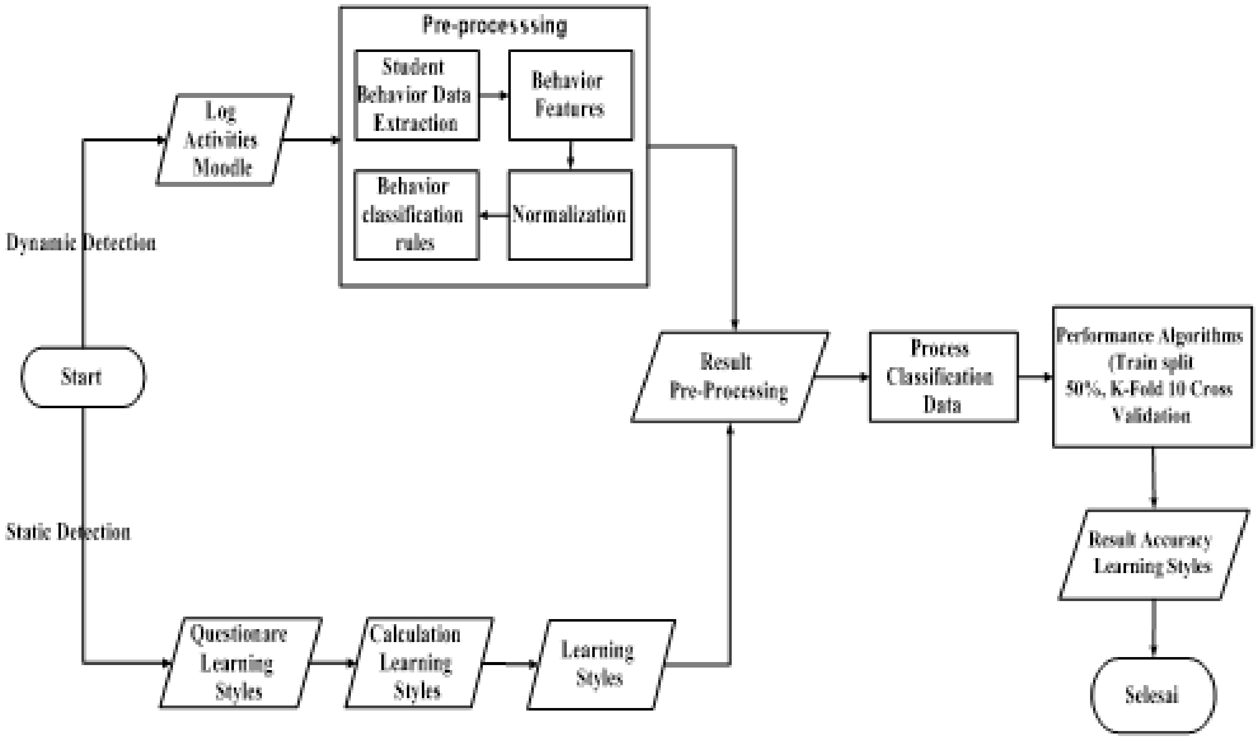

FIGURE 1 The proposed system design.

Other studies focused on introducing student behavior models in order to detect student learning styles. Heidrich et al.[13] discussed studies related to a model capable of integrating data generated from student behavior in ODL with cognitive aspects of learning styles by crossing LLT with LLS. Another study by Bajaj and Sharma[14] discussed studies on the combined theoretical learning model. It compared the results with the Decision Tree and Multilayer Perceptron methods. Lastly, Costa et al.[15] discussed studies related to observing the behavior of distance education student attempt behavior. Interact with Virtual Learning Environments and associate them with their CHAEA-identified learning styles. The administered relationship style was investigated.

The purpose of this paper is to present a learners' statistical analysis of dynamic student behavior on the LMS. In e-learning, learning styles are generated based on the total number of student visits to learning objects. The proposed method is based on FSLSM's four dimensions. Classification methods are Decision Tree, Naïve Bayes, and K-Nearest Neighbor. This model is written in Python, and the accuracy was calculated using a train split value of 80:20 and a k-fold value of 10 cross-validations.

3 | MATERIAL AND METHOD

The research methodology used in the system design shown in Fig. 1 is to encounter LMS using (ILS) questionnaire) as the common goal of prediction. The student learning behavior is used to detect learning styles automatically by LMS users, and learning style data obtained through questionnaires is used as a learning style label.

3.1 | Static Detection

Detecting student learning styles from statistical detection, based on the results of questionnaire data collection, is then calculated into learning styles.

TABLE 1 The category of question index of learning style (ILS) Felder-Silverman.

Learning Style	Questionnaire ILS (Answers A)	Learning Style	Questionnaire ILS (Answers B)
Active	1, 17, 25, 29 5, 9, 12, 21, 33, 37,41	Reflective	1, 5, 17, 25, 29 9, 13, 21, 33,37, 41
Sensing	2, 30, 34 6,10,14, 18,26,38 22, 42	Intuitive	2,14,22,26,30,34, 6, 10, 18, 38 42
Visual	3,7,11, 15, 19, 23, 27, 31, 35, 39, 43	Verbal	3, 7, 15, 19, 27, 35, 3, 7, 11, 23, 31, 39, 43
Sequential	4,28, 40 20, 24, 32, 36, 44, 8, 12, 16	Global	4, 8, 12, 16, 28, 40, 24, 32 20, 36, 44

3.1.1 | Complete the Index of Learning Style (ILS) Questionnaire

This stage is the first stage of data collection by conducting a survey. The survey was performed using the technique from the Felder model[3] as a reference for modeling learning styles. The questionnaire on the FSLSM model consists of 44 questions that will represent the style filled out by students using the LMS. The contents of the questionnaire used.

3.1.2 | Learning Styles Calculation

The LMS user learning style is calculated at this stage. The completed questionnaire data is calculated based on a predetermined threshold. A range of values from +11 to -11 is provided for each dimension, with 11 questions representing one dimension. For example, to measure learning style preferences using FSLSM, a range of deals from +/-2 is given, with each question having two answer choices (A or B) used to measure the likes to be detected.

The following is an example of converting questionnaire responses into active, then "+1," and the reflective learning style, then "-1." By calculating all the questions representing each dimension, it is possible to conclude that in each dimension.

$$ILS\ Score = Larger - Small + Letter\ of\ Larger \tag{1}$$

For example, student A answers 5A and 8B for the processing dimension, so 8B-5A = 3. Question b is more significant than a, which will be considered 3b. The conclusion is that student A has a reflective learning style in the processing dimension.

3.1.3 | Learning Style

Learning styles from the calculation results are adjusted and classified according to their dimensions according to Felder-Silverman Learning Style Model. Based on the style table classification learning, we can get patterns to form datasets based on object learning that is used as an attribute/feature related to FSLSM. Learning style based on FSLSM into 4 dimensions, namely Processing (Active & Reflective), Input (Verbal & Visual), Perception (Sensing & Intuitive) and Comprehension (Sequential & Global).

3.2 | Dynamic Detection

Detecting student learning styles from dynamic detection is based on the results of Moodle LMS activity log, preprocessing, and classification data.

3.2.1 | Moodle LMS Activity Log

At this stage, the log data is collected for three months using the LMS of Petra Christian Petra School at https://lms.pppkpetra.sch.id. This log data contains time, user's full name, affected user, context, component, event name, description, origin, and IP address. The log data collected will go through the preprocessing stage first to be categorized into learning behavior patterns before being classified using machine learning.

User full name	Affected user	Event context	Component	Event name	Description	Origin	IP address
SANTI TIODORA SIANTURI (GURU SMK)	-	Course: Administrasi Sistem Jaringan Kelas 12 TKJ-2	System	Course viewed	The user with id '1083' viewed the course with id '35280'.	web	36.82.17.82
CHRESTA NATHANAEL	-	Course: Administrasi Sistem Jaringan Kelas 12 TKJ-2	System	Course viewed	The user with id '17454' viewed the course with id '35280'.	web	114.5.108.43
CHRESTA NATHANAEL	CHRESTA NATHANAEL	Attendance: Absensi siswa	Attendance	Session report viewed	User with id 17454 viewed attendance sessions for	web	114.5.108.43

FIGURE 2 The moodle log data ujsed in this study.

TABLE 2 The result of extracting the behavior features.

User Full Name	Event Context	Event Name
EDWARDUS EFRATA SUDI MARANATHA	Course : Administrasi Sistem Jaringan	System
MOCH. ADITYA RACHMADAN SMK-11TKJ2	Course : Administrasi Sistem Jaringan	System
GARRY GARCIA HANDI PUTRA SMK-11 TKJ 2	Course : Administrasi Sistem Jaringan	System
HENDI SMK-11 TKJ 2	Course : Administrasi Sistem Jaringan	System
EZRA AUGUSTINUS	Quis: UH2	Quiz

3.2.2 | Preprocessing

This stage is processing raw data taken from the Moodle log. There are four main processes. The first process is extraction of student behavior data. There is a data cleaning process, feature extraction, and threshold implementation in the preprocessing stage. The data cleaning process ignores unused attributes such as the Time column, affected user, component, description, origin, and IP address in the Moodle activity log and removes users (students who did not fill out the questionnaire). Students' actions express the attributes in Fig. 2 .

The second process is behavior features selection. This process selects features to log files that fit styles. Students' automatically saved Moodle after they finished studying in E-Learning.

The third process is normalization. In this process, the students' log data collected will be compared. Subsequently, the relationship between dimensions was discovered using the Behavior Classification Rules.

The last process is rules of behavior classification. In this process, the features will be mapped based on their dimensions according to Felder Silverman's Learning Style Model. Based on the learning style classification rules, we can get patterns to form datasets based on learning objects used as attributes/features related to FSLSM. There are four dimensions of learning style based on FSLSM. Another hand, text, image, and video learning objects are classified as the input dimension. Examples and assignment learning objects are part of the perception dimension. Navigation and course overview learning objects are part of the understanding dimension.

TABLE 3 The rules of classification learning style based on student's behavior.

Learning Object	Learning Style	Relevant Object	Dimension
Text	Verbal	Visit	Input
	Visual	No visit	
Powerpoint	Visual	Visit	
	Verbal	No Visit	
Video	Visual	Visit	
	Verbal	No Visit	
Picture	Visual	Visit	
	Verbal	No Visit	
Forum	Active	Post/Reply	Processing
	Reflective	Reflective	
Chat	Active	Post	
	Reflective	Review	
Demo	Active	Run	
	Reflective	View	
Example	Visit	Sensor	Perception
	No Visit	Intuitive	
Assignment	Submit	Sensor	
	View	Intuitive	
Navigation	Navigating Linearly	Sequential	Understanding
	Navigation Globally	Global	
Course Overview	View	Global	
	No View	Sequential	

TABLE 4 The dataset attributes.

#	Attribute	Description
1	No	Number
2	NAME	Names of students
3	TEXT	The number of actions on the learning object "Text" in Moodle
4	POWERPOINT	The number of actions on the learning object "PowerPoint" in Moodle
5	VIDEO	The number of actions on the learning object "Video" in Moodle
6	PICTURE	The number of actions on the learning object "Picture" in Moodle
7	FORUM	The number of actions on the learning object "Forum" in Moodle
8	CHAT	The number of actions on the learning object "Chat" in Moodle
9	DEMO	The number of actions on the learning object "Demo" in Moodle
10	EXAMPLE	The number of actions on the learning object "Example" in Moodle
11	ASSIGNMENT	The number of actions on the learning object "Assignment" in Moodle
12	NAVIGATION	The number of actions on the learning object "Navigation" in Moodle
13	COURSE OVERVIEW	The number of actions on the learning object "Course Overview" in Moodle
14	DIMENSION	Label Class

The dataset consists of 14 attributes and 1 class label. Class labels consist of Processing, Input, Perception, and Understanding, used as targets/goals for the classifier model.

3.2.3 | Classification Data

The classification process looks for patterns or information from the data with the chosen technique to predict the desired class label/goals [16]. In this research, the classification process to classify the level of non-compliance of motor vehicle taxpayers based on tax papers.

Decision Tree Classifier (DT) [17] is a classification method for carrying out the decision-making process by changing data/tables into branching forms/trees. The entropy function is used to determine the branching of the Decision Tree. Eq. 2 represents the Entropy function.

$$Entropy(s) = \sum_{i=1}^{n} p_i \log_2(p_i) \tag{2}$$

$$Gain(S, A) = entropy(S) - \frac{|S_i|}{s}\, entropy(S_i) \tag{3}$$

Where S is the set of cases, n in the entropy value equation means the number of partitions S, n in the equation the gain value indicates the number of partitions attribute A, and A is the feature, pi is the proportion of S_i to S. The value of $|Si|$ is the proportion of S_i to S, as well as $|S|$ is the number of S cases.

Naïve Bayes is a machine learning method calculated based on Bayes' theorem. The idea of this method is that each attribute in a given category is assumed to be an independent attribute that has nothing to do with other attributes or is called the conditional independence class[18]. The equation of Bayes' theorem can be written in Eq. 3.

$$P(B|A) = \frac{P(B|A)\ P(A)}{P(B)} \tag{4}$$

Where $P(A|B)$ is the posterior probability of A in condition B or called the posterior probability, $P(B|A)$ is the posterior probability of B in condition A or called likelihood, and $P(A)$ is the prior probability of A or commonly referred to as class prior probability, and $P(B)$ is the prior probability of B or called predictor prior probability.

Nearest Neighbour (KNN) is a classification method that compares testing data and training data[4]. The principle of the KNN method is to find the k-value of the nearest neighbor or the most similarity between the training data and the testing data. This method also uses a measure of similarity as a comparison between training data and testing data, using the Euclidean distance formula to measure the distance between two points. The Euclidean distance formula can be written with Eq. 5[19].

$$d(X_{train}, X_{test}) = \sqrt{\sum_{(i,j=1)}^{n} X_{train,i} - X_{test,j})^2} \tag{5}$$

Where $d(X_{train}, X_{test})$ is the Euclidean distance between two dataset, The $X_{train,i}$ is the i-th training data, $X_{test,j}$ is the j-th testing data, n is the lot of data, and i, j is a constant value between $1, 2, 3 \ldots n$.

3.2.4 | Classification Algorithms Performance

The percentage split test is a test method that divides the dataset into training sets and test sets based on the desired percentage. K-fold cross-validation is a test method in which a dataset is divided into several partitions, the so-called fold. During k-iteration, one-fold is selected as the test set, and the remaining folds are chosen as the training set.

The confusion matrix is one of the tools that displays and compares the actual value with the predicted model value that can be used to generate evaluation metrics, i.e., accuracy, precision, recall, and f1-score[17]. The results of the classification process in the confusion matrix are true positive (TP), true negative (TN), false positive (FP), and false negative. Accuracy is determined by dividing the number of positive data predicted to be positive and negative data predicted to be negative by the total amount of data in the dataset (3). Precision shows the amount of data predicted to be in a positive category, which belongs to the positive category (4). Recall shows the amount of data in the positive category correctly predicted in the positive category (5). The f1 score is obtained from precision and recall results between the predicted and actual categories (6).

$$Accuracy = \frac{TP + TN}{TP + TN + TP + FN} \tag{6}$$

$$Precision = \frac{TP}{TP + FP} \tag{7}$$

$$Recall = \frac{TP}{TP + FN} \tag{8}$$

$$F1\text{-}score = \frac{Precision \times Recall}{Precision + Recall} \tag{9}$$

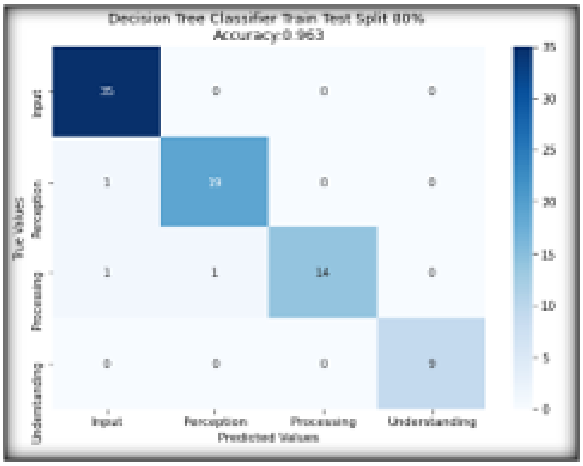

FIGURE 3 The confusion matrix of Decision Tree using 80:20 split.

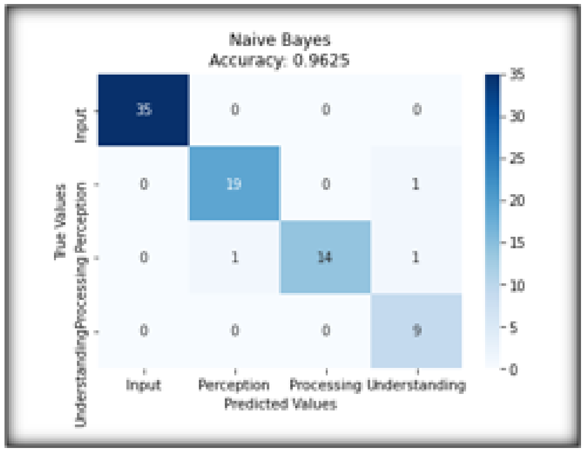

FIGURE 4 The confusion matrix of Naive Bayes using 80:20 split.

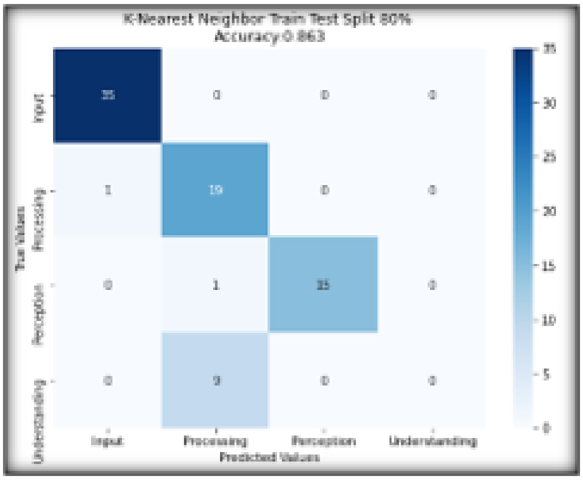

FIGURE 5 The confusion matrix of KNN using 80:20 split.

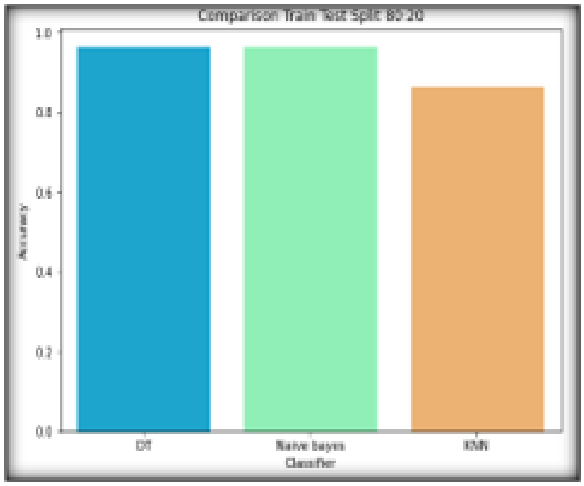

FIGURE 6 The comparison of confusion matrix between the three classifier using 80:20 split.

4 | RESULTS AND DISCUSSION

The created dataset was tested using Jupyter Notebook software, Python programming language version 3.8.5, and scikit-learn version 0.24.2. The dataset was tested using percentage train split test 80:20 and 10-fold cross-validation, using the Decision Tree, Naïve Bayes, and KNN classification algorithms.

There are two tests carried out, namely:

1. Classification methods such as Decision Tree, Naïve Bayes, and K-Nearest Neighbor that have been trained are carried out using the train_test_split function in the sklearn library with a data ratio of 80:20.

2. Classification methods such as Decision Tree, Naïve Bayes, and K-Nearest Neighbor using the K-Fold 10 cross-validation method. Ten-fold Cross Validation is one of the recommended K-fold Cross validations for selecting the best model.

The test results of the Decision Tree, Naive Bayes, and k-Nearest Neighbor test results using an 80:20 split train test will be shown in Fig. 3 - 6 .

The test results of the Decision Tree, naive Bayes, and k-Nearest Neighbor using k-fold ten cross-validations will be shown in Fig. 7 - 10 .

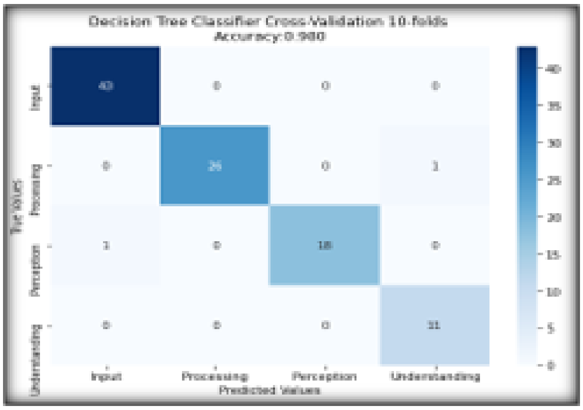

FIGURE 7 The confusion matrix of Decision Tree using k-fold split.

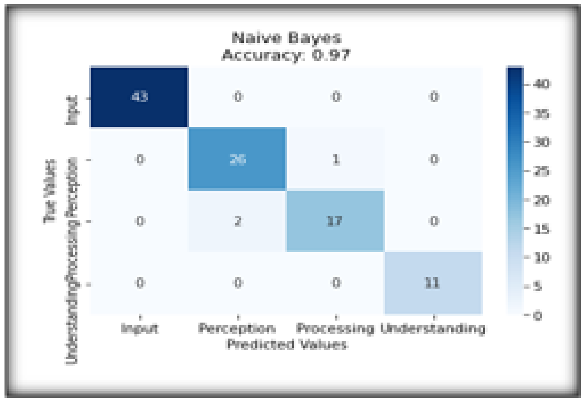

FIGURE 8 The confusion matrix of Naive Bayes using k-fold split.

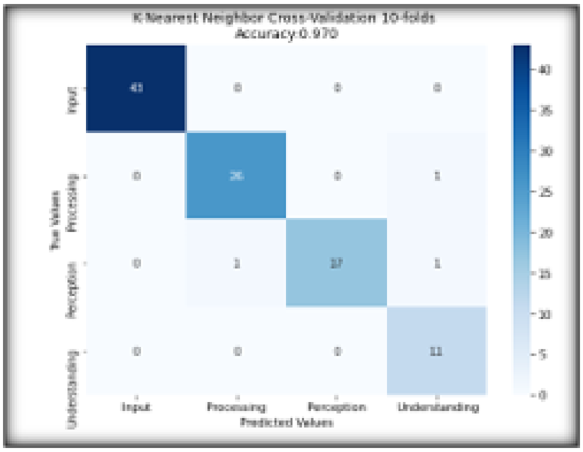

FIGURE 9 The confusion matrix of KNN using k-fold split.

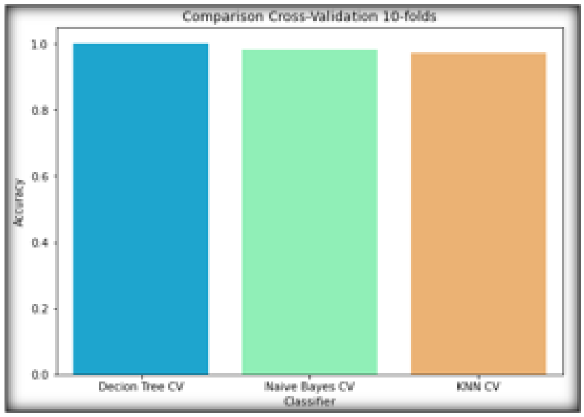

FIGURE 10 The comparison of confusion matrix between the three classifier using k-fold split.

TABLE 5 The accuracy and computation time.

Testing	Algorithm	Precision				Accuration	Time
		Input	Perception	Processing	Understanding		(sec)
Train Split Test 80:20	Decision Tree	0.95	0.95	1.00	1.00	0.96	0.000998
	Naïve Bayes	1.00	0.95	1.00	0.82	0.96	0.001584
	KNN	0.97	0.66	1.00	0.00	0.86	0.000960
K-Fold 10 Cross Validation	Decision Tree	0.98	1.00	1.00	0.92	0.98	0.040332
	Naïve Bayes	1.00	0.93	0.94	1.00	0.97	0.008958
	KNN	1.00	0.96	1.00	0.85	0.97	0.054300

Based on the test results shown in Table 5 , the Decision Tree algorithm produces the highest accuracy, processing time, precision, recall, and f1-score in classifying the level of learning styles. On the other hand, KNN produces the lowest accuracy, processing time, precision, recall, and f1-score. And Based on the confusion matrix of the Decision Tree algorithm, 43 Input students, 26 Processing students, 17 Perception students, and 11 Understanding students were obtained.

5 | CONCLUSION

In this study, we present a new literature-based method for estimating learners' automatic and dynamic learning styles. Statistically based on the ILS questionnaire and dynamically based on analyzing student behavior on the LMS. Learning styles are generated from the total visits of students to learning objects in e-learning. The resulting learning style results are used as labels on the dataset. The proposed method refers to the four dimensions of FSLSM, namely Process (Active/Reflective), Input (Visual/Verbal), Perception (Sensor/Intuitive), and Comprehension (Sequential/Global).

The method used for classification is to use three classifications: Decision Tree, Naïve Bayes and K-Nearest Neighbor. We have evaluated this model using Python and sklearn, where there are two types of tests, namely 80:20 train split and K-Fold 10 Cross-Validation. The results of the study showed that the Decision Tree method could better detect and predict learning styles, namely using the 80:20 train split test, which obtained an accuracy of 0.96 process time of 0.000998 seconds, while the K-Fold 10 Cross-Validation test obtained an accuracy of 0.98 and a processing time of 0.04033 seconds.

For the future research, it is recommended to use more datasets and better machine learning methods that are more varied to compare and find the best method in terms of precision and accuracy.

This study uses a dataset that has a distribution of the number of students for each category which is not balanced. The category with the highest number of documents is the Input category indicates that students tend to access these input categories more often. This research still cannot overcome the problem of balanced data because the text categorization method can identify the majority class well but have difficulty identifying the minority class resulting in a decrease in recall in the minority class and a high recall value for the majority class. Therefore, for further research, a method that can be applied to overcome the problem of unbalanced data and used multi-label text categorization to detect interrelationships between dimensions to improve the performance of the categorization method text is optimized.

CREDIT

Santi Tiodora Sianturi: Data Curation, Writing - Original Draft, Validation, and Investigation. **Umi Laili Yuhana:** Conceptualization, Methodology, Formal Analysis, Writing - Review & Editing, and Supervison.

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