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SINGLE-LABEL LEARNING STYLE CLASSIFICATION USING MACHINE LEARNING WITH GRIDSEARCH-BASED HYPERPARAMETER TUNING ON LMS BEHAVIORAL DATA

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Abstract
The rapid growth of online learning environments has increased the importance of Learning Management Systems (LMS) as a rich source of behavioral data for learning analytics. One learner characteristic that strongly influences learning effectiveness is learning style; however, traditional questionnaire-based identification approaches suffer from subjectivity, limited scalability, and static representation. To address these limitations, this study proposes a machine learning-based approach for automatic learning style classification using LMS behavioral data grounded in the Felder–Silverman Learning Style Model (FSLSM). This study utilizes LMS activity log data collected from Universitas Siber Asia over three academic years (2022–2024). The dataset consists of 5,633 student interaction records with 72 raw behavioral attributes, which were preprocessed, aggregated, and transformed into 12 representative behavioral features reflecting students' interactions with learning materials, assessments, discussions, multimedia resources, and navigation patterns. A rule-based FSLSM mapping mechanism was applied to generate 16 learning style profiles, which were treated as targets in a single-label classification setting. Support Vector Machine (SVM) and Gradient Boosting (GB) classifiers were implemented and optimized using feature selection and GridSearch-based hyperparameter tuning. The dataset was divided into 75% training data and 25% testing data using a stratified split to preserve class distribution. Experimental results show that Gradient Boosting consistently outperforms SVM across all evaluation metrics. The GB model achieved an accuracy of 0.84 and a macro F1-score of 0.79, demonstrating strong generalization capability and robustness to class imbalance. In contrast, SVM exhibited lower and less stable performance, particularly on minority learning style classes. These findings confirm that

ensemble-based methods such as Gradient Boosting are more effective for LMS-based single-label learning style classification and support the feasibility of automatic FSLSM-based learning style detection for data-driven adaptive learning systems.

1.0 INTRODUCTION

The rapid growth of online learning environments has significantly increased the role of Learning Management Systems (LMS) in higher education. LMS platforms record detailed behavioral data generated from students' interactions with learning materials, assessments, and collaborative activities, enabling large-scale analysis of learning processes through learning analytics and educational data mining. Recent studies highlight that LMS behavioral data provide valuable insights into students' engagement patterns, learning strategies, and academic performance, which are difficult to capture using traditional evaluation methods alone [1] [2].

One important learner characteristic that strongly influences learning effectiveness is learning style. One important learner characteristic that strongly influences learning effectiveness is learning style. Learning style reflects an individual's preference in perceiving, processing, and organizing information during learning activities. Among various learning style models, the Felder–Silverman Learning Style Model (FSLSM) has been widely adopted in technology-enhanced learning research due to its clear multidimensional structure and strong relevance to learning behaviors in engineering and computer-based education. FSLSM characterizes learners across four bipolar dimensions, active–reflective, sensing–intuitive, visual–verbal, and sequential–global allowing a comprehensive representation of learners' cognitive and behavioral preferences. In online learning settings, especially in self-paced and asynchronous environments, understanding learning styles based on such multidimensional models becomes increasingly important to support personalization and adaptive learning systems. However, many LMS-based learning systems still deliver instructional content uniformly, without considering individual differences among learners, which can negatively affect learning outcomes and student satisfaction [3].

Traditionally, learning styles have been identified using self-reported questionnaires or surveys. Although widely used, questionnaire-based approaches suffer from several limitations, including subjectivity, response bias, and low scalability in large online learning environments. Furthermore, learning styles may evolve over time, making static questionnaire results less reliable for continuous personalization. As a result, recent research has shifted toward data-driven approaches that infer learning styles automatically from learners' actual behavior recorded in LMS platforms[4],[5].

Machine learning techniques have been increasingly applied to analyze LMS behavioral data due to their ability to model complex, non-linear relationships between learning activities and learner characteristics. Previous studies have demonstrated that machine learning models can effectively classify or predict learning-related attributes, such as engagement levels, academic performance, and learning preferences, using features derived from access logs, assessment activities, and interaction patterns [6],[7]. Nevertheless, empirical evidence comparing different machine learning algorithms for FSLSM based learning style classification using real LMS behavioral data remains limited, particularly in terms of model optimization and systematic evaluation.

Moreover, many existing studies focus on a single machine learning model or employ limited feature selection strategies, which may restrict model generalization and robustness. There is still a lack of studies that comprehensively evaluate optimized machine learning models for learning style classification by combining feature selection, hyperparameter tuning, and rigorous performance assessment. Addressing this gap is essential to ensure that learning style detection models are reliable and applicable in real-world LMS environments.

Therefore, this study proposes a machine learning-based approach for learning style classification using LMS behavioral data grounded in the Felder–Silverman Learning Style Model. Support Vector Machine (SVM) and Gradient Boosting (GB) classifiers are employed and optimized through feature selection and GridSearch-based hyperparameter tuning. By systematically comparing the performance of these models, this research aims to provide empirical evidence on the effectiveness of machine learning techniques for automatic FSLSM-based learning style classification and to contribute to the development of data-driven adaptive learning systems in online education.

2.0 RELATED WORK

The application of machine learning techniques in Learning Management System (LMS) environments has gained increasing attention in recent years, particularly for analyzing student behavior and predicting learning-related outcomes. LMS platforms generate extensive behavioral data, including access frequency, assessment participation, content interaction, and navigation patterns, which can be exploited to model learner characteristics in an objective and scalable manner. Several recent studies have confirmed that behavioral features extracted from LMS logs are effective predictors for various educational tasks, such as academic performance prediction, engagement analysis, and learner profiling [6],[8].

In the context of learning style identification, early research predominantly relied on questionnaire-based instruments. However, due to issues related to subjectivity, response bias, and limited scalability, recent studies have shifted toward data-driven approaches that infer learning styles directly from learners' interaction data. The systematic review automatic learning style prediction studies and concluded that machine learning-based approaches using behavioral data have become the dominant trend, particularly in online learning environments [9].

Most existing machine learning-based learning style studies adopt a single-label classification approach, where each learner is assigned to one dominant learning style category. For example, the application of ensemble tree-based classifiers for predicting students' learning styles under the Felder–Silverman model using LMS interaction data has demonstrated that supervised learning methods can achieve satisfactory classification accuracy when sufficient behavioral features are available [10]. Traditional classification algorithms, including Support Vector Machine and Decision Tree, have been shown to effectively classify learning styles in e-learning environments when supported by appropriate feature engineering techniques [11]

Several studies have emphasized the importance of algorithm selection and feature optimization in single-label learning style classification. The effectiveness of single-label learning style classification has been widely reported to depend on appropriate algorithm selection and model optimization, as learning style prediction in MOOC environments is strongly influenced by feature relevance and parameter configuration, while the application of feature selection and hyperparameter tuning has been shown to significantly enhance classification performance in educational datasets, indicating that optimization is a crucial step for reliable learning style detection [12],[13].

Despite these advances, limitations remain evident in the existing literature. First, many studies focus on a single classifier without conducting systematic comparisons between different machine learning algorithms, making it difficult to assess relative strengths and weaknesses. Second, some works treat feature selection and hyperparameter tuning as secondary steps, even though these processes directly affect model robustness and generalizability. Third, although LMS behavioral data are widely used, empirical studies that comprehensively evaluate optimized single-label classifiers for learning style classification using real LMS data are still limited.

Table 1 summarizes representative studies on learning style classification, highlighting the learning style models, data sources, classification methods, key findings, and research gaps. The comparison reveals that while LMS-based machine learning approaches are promising, systematic evaluations of optimized single-label classifiers remain limited, motivating this study's comparative analysis of optimized SVM and Gradient Boosting models.

Based on these observations, this study positions itself within the single-label learning style classification paradigm by systematically comparing optimized Support Vector Machine and Gradient Boosting models using LMS behavioral data. By integrating feature selection and GridSearch-based hyperparameter optimization, this research aims to strengthen empirical evidence on the effectiveness of machine learning techniques for automatic learning style classification in online learning environments.

Table 1. Comparative Analysis of Related Studies on Single-Label Learning Style Classification Using LMS Data

Author(s)	Learning Style Model	Data Source	Classification Method (Single Label)	Main Findings	Research Gap
[10]	Felder–Silverman	LMS interaction logs	Ensemble tree-based classifiers	Supervised classifiers achieved satisfactory accuracy using behavioral features	No comparison with non-tree models; limited analysis of feature selection and hyperparameter optimization
[11]	Learning style categories	E-learning system data	SVM, Decision Tree	Traditional classifiers performed effectively with engineered features	Model optimization and systematic comparison were not explored
[12]	Learning style categories	MOOC behavioral data	Machine learning classifiers	Classification performance strongly depended on feature relevance and parameter configuration	Focused on a single learning context; lacked comparative evaluation across classifiers
[14]	Educational categories	Educational datasets	Optimized ML classifiers	Feature selection and hyperparameter tuning significantly improved performance	Not explicitly focused on learning style classification
[9]	Multiple learning style models	Survey of LMS-based studies	Review of ML approaches	Single-label classification dominates learning style prediction research	Conceptual review without experimental validation
[5]	Learning preference categories	LMS navigation and interaction data	Supervised machine learning classifiers	LMS navigation and interaction features were effective in modeling learner preferences and behavior patterns	Learning styles inferred indirectly; not explicitly mapped to established learning style models
[7]	Learning style indicators	LMS behavioral and activity logs	Machine learning classifiers	Behavioral features from LMS logs enabled accurate classification of learner characteristics	Focused primarily on performance prediction rather than learning style classification
[6]	Learning-related categories	LMS interaction data	Supervised machine learning models	LMS behavioral data provided reliable indicators for learner profiling and classification tasks	Learning style classification was not the main focus; limited model comparison
This study	Felder–Silverman	LMS behavioral data	Optimized SVM & Gradient Boosting	Comparative evaluation of optimized single-label classifiers for learning style classification	Focus limited to single-label scope

3.0 METHODOLOGY

3.1 Proposed Model

This study proposes a machine learning-based framework for single-label learning style classification using LMS behavioral data. The proposed model integrates dataset development and classification processes to ensure systematic and reliable learning style identification, as illustrated in Figure 1.

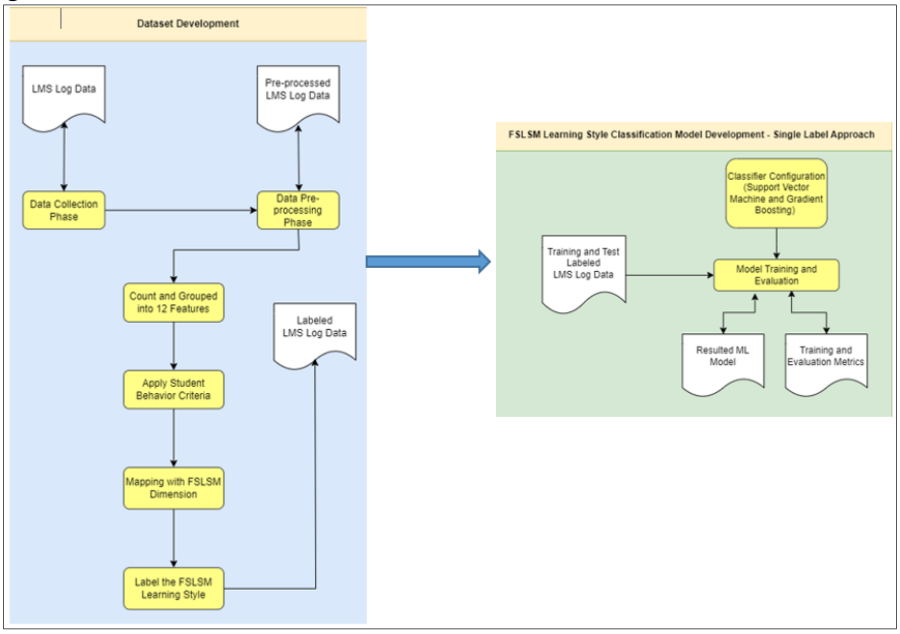

Figure 1. Research framework FSLSM Learning style single label classification approach

Figure 1 illustrates the overall research methodology adopted in this study, which is structured into two main stages: Dataset Development and Single-Label Learning Style Classification Model Development. This framework ensures a systematic transformation of raw LMS behavioral data into a validated machine learning model for learning style classification.

The first stage focuses on constructing a learning style dataset from raw LMS log data. LMS behavioral data are initially collected from various learning activities, including course access, multimedia usage, assessments, forums, and synchronous learning sessions. This phase aims to capture authentic learning behaviors generated during students' interactions with the LMS. Following data collection, a data preprocessing phase is conducted to handle missing values, normalize numerical features, and remove irrelevant or redundant attributes. The cleaned dataset is then subjected to feature aggregation and counting processes to derive meaningful behavioral indicators, such as access frequency, participation intensity, and assessment-related activities. To generate learning style labels, behavioral features are mapped to learning style dimensions using predefined criteria. These criteria are designed to reflect dominant behavioral tendencies observed in LMS interactions. The mapped features are subsequently aggregated according to the selected learning style framework, resulting in labeled learning style data. This process produces a finalized dataset that combines LMS behavioral features with corresponding learning style labels, which serves as the input for the classification stage.

The second stage involves developing and evaluating a machine learning model for single-label learning style classification. The labeled dataset is first divided into training and testing subsets to ensure an unbiased evaluation of model performance. Feature selection is then applied to reduce dimensionality and retain the most relevant behavioral attributes, thereby improving model efficiency and generalization. Next, machine learning classifiers are trained using the selected features. Model optimization is performed through systematic hyperparameter tuning to identify the most effective parameter configurations. The optimized models are subsequently evaluated using the testing data to assess their classification performance.

Finally, the results of model training and evaluation are analyzed to determine the effectiveness of the proposed approach in accurately classifying learning styles based on LMS behavioral data. This structured methodology ensures that the classification process is data-driven, reproducible, and suitable for real-world LMS-based learning analytics applications.

3,2 Data Collection Phase

The dataset used in this study was obtained from the Learning Management System (LMS) activity logs of Universitas Siber Asia, which record all student interactions during online learning sessions. The data collection process was carried out over a period of three academic years, from 2022 to 2024, thereby ensuring that the dataset captures variations in learning behavior across multiple cohorts and course implementations

The final dataset consists of 5,633 records and 72 features that objectively represent students' learning behaviors, including activities such as reading course materials, watching instructional videos, downloading documents, participating in discussion forums, and completing quizzes and assignments. Each data entry includes student identification information, the specific course enrolled, the corresponding learning session, and a series of text-based, visual-based, navigational, and assessment-related activities**.**

3.3 Data Pre-Processing Phase

The pre-processing stage transforms raw LMS log data into a structured dataset suitable for analysis. The process starts with importing LMS logs consisting of 72 attributes collected between 2022 and 2024, followed by data cleaning to remove duplicates, handle incomplete records, and standardize timestamps. Session reconstruction is then applied to consolidate various learning activities into coherent student-level sessions, while data integration aligns all LMS modules into a unified format. Subsequently, derived behavioral indicators such as activity frequency and assessment-related measures are generated. Finally, the original 72 attributes are aggregated into 12 representative behavioral features reflecting core learning activities, as illustrated in Figure 2

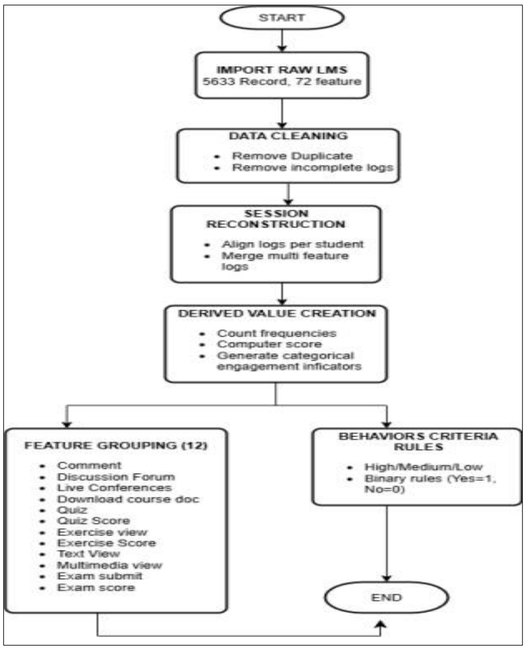

Figure 2. Pre-processing phase

Finally, behavior criteria rules are applied using threshold-based (High/Medium/Low) and binary (1=Yes / 0=No) logic to convert raw counts into standardized behavioral categories. The resulting pre-processed dataset is clean, structured, and ready for feature engineering and FSLSM-based learning style classification. The FSLSM framework classifies learners along four dimensions: Perception (Sensing/S, Intuitive/N), Processing (Active/A, Reflective/R), Input (Visual/V, Verbal/B), and Understanding (Sequential/Q, Global/G). When combined, these dimensions generate 16 unique learning-style profiles, each reflecting different patterns of learning behavior. The results of the 16 combinations of Felder Silverman's learning styles model can be seen in Table 2. Identifying these profiles is essential for adaptive instruction in programming courses, where students often demonstrate diverse approaches to problem-solving and engagement.

Table 2. Combination Of Felder Silverman Learning Style Model

No	Code LS	Dimension	No	Code LS	Dimension
1	LS-1	A-S-V-Q	9	LS-9	A-N-V-G
2	LS-2	A-S-V-G	10	LS-10	A-N-V-G
3	LS-3	A-S-B-Q	11	LS-11	A-N-B-Q
4	LS-4	A-S-B-G	12	LS-12	A-N-B-G
5	LS-5	R-S-V-Q	13	LS-13	R-N-V-Q
6	LS-6	R-S-V-G	14	LS-14	R-N-V-G
7	LS-7	R-S-B-Q	15	LS-15	R-N-B-Q
8	LS-8	R-S-B-G	16	LS-16	R-N-B-G

In this study, the 16 profiles are operationalized as pseudo-labels for downstream modeling using single-label and multi-label classification approaches based on Support Vector Machine and Gradient Boosting, as specified in the research framework. The rule-based mapping that generates these profiles provides a rigorous linkage between LMS behavioral indicators and FSLSM theoretical constructs, ensuring methodological validity and supporting personalized learning within the LMS environment.

3.4 Data Labeling and Feature Extraction

This subsection describes the Data Labeling and Feature Extraction procedures, which are essential for transforming raw LMS interaction logs into structured inputs suitable for machine learning. Through these steps, each learner's behavior is mapped to FSLSM indicators and represented through a set of well-defined features.

Table 3. Behavioral feature transformation and categorization rules

Dimension	Feature	Student Behavior	Dimension	Feature	Student Behavior
Processing	Comment	Number of comment > 6 (High)	Perception	quiz	Attempt or complete quiz (Yes)
		Number of comment 1 - 5 (Moderate)			Did not Attempt or complete quiz (No)
		Number 0 (Low)		Score quiz	Score quiz >= 80 (High)
	Discussion forum	Participated = 0 (No)			Score quiz 30 – 80 (Moderate)
		Participated > 0 (Yes)			Score quiz < 30 (Low)
	Live conference	Participated = 0 (No)		Exercise	Attempt or complete excercise (Yes)
		Participated > 0 (Yes)			Did not Attempt or complete excercise (No)
	Download documents	Download > 10 (High)		Score exercise	Score quiz >= 80 (High)
		Download 3 – 9 (Moderate)			Score quiz 30 – 80 (Moderate)
		Download < 3 (Low)			Score quiz < 30 (Low)
Input	Multimedia views	Multimedia views >=3 (High)	Understanding	Score Exam	Score exam >= 75 (High)
		Multimedia views < 3 (Low)			Score exam 40 – 75 (Moderate)

Dimension	Feature	Student Behavior	Dimension	Feature	Student Behavior
	Text course views	Text course views >= 5 (High)			Score exam < 40 (Low)
		Text course views 2 – 5 (Moderate)		Exam Submit	Attempt or complete Exam (Yes)
		Text course views < 2 (Low)			Did not Attempt or complete Exam (No)

Table 3 presents the behavioral coding scheme used to transform raw LMS logs into structured indicators relevant to this study and to the Felder–Silverman Learning Style Model (FSLSM). The table organizes student behaviors into four dimensions—Processing, Perception, Input, and Understanding—each linked to specific LMS features. For every feature, clear operational rules were defined to classify activity levels as High, Moderate, or Low, or into binary indicators (Yes/No). These standardized thresholds ensure consistent interpretation of behavioral patterns and enable accurate mapping of LMS interactions to the corresponding FSLSM dimensions in the learning style classification process.

The Processing dimension quantifies engagement through comments, forum participation, live sessions, and document downloads using thresholds that classify activity as High, Moderate, or Low. The Perception dimension captures performance-related behaviors, including quiz and exercise attempts and scores which are categorized similarly and supplemented with Yes/No indicators to show whether a learner attempted the activity. The Input dimension reflects learning preferences based on the frequency of multimedia versus text-based material views. The Understanding dimension includes exam scores and submission status, categorized into performance levels or binary indicators.

Overall, this scheme (1) reduces the complexity of the 72 raw LMS features into concise behavioral indicators and (2) supports systematic mapping of student behaviors to the Felder–Silverman Learning Style Model (FSLSM). The use of standardized thresholds ensures consistent interpretation across all records and strengthens the reliability of the subsequent classification process

4.0 RESULT

The results section presents the empirical findings derived from the modeling pipeline, which includes data preprocessing, feature transformation, rule-based FSLSM mapping, and the subsequent implementation of single-label classification algorithms. For both the Support Vector Machine (SVM) and Gradient Boosting experiments, the dataset was divided into 75% training data and 25% testing data using a stratified splitting strategy to preserve the original distribution of learning style labels. This section summarizes the performance of each model based on standard evaluation metrics such as accuracy, precision, recall, and F1-score alongside supporting analyses including confusion matrices, correlation structures, and feature behavior across the four FSLSM dimensions. The reported results aim to provide clear evidence of how effectively the proposed approach identifies learners' FSLSM profiles from LMS behavioral logs and to highlight the robustness, consistency, and limitations observed during experimentation.

4.1 Experiment 1 : Support Vector Machine (SVM) Singgle Label Classification

In the single-label classification experiment, a SVM was used to predict 16 FSLSM learning style profiles (LS1–LS16) based on student behavior features extracted from LMS logs. The model training process was carried out using a pipeline scheme that integrates Min–Max feature scaling, feature selection, and SVM classifiers, with the best parameter configuration obtained through GridSearchCV and Stratified K-Fold Cross-Validation (k = 5). Based on the optimization results, the best model combination was obtained using a SelectPercentile with the top 70% of features, an SVM kernel with parameters C = 1 and γ = 1, and a class weight that is adjusted to reduce the impact of class imbalances.

The parameterization process involved 400 model training combinations, with a computation time of approximately 261 seconds, demonstrating the complexity of SVM modeling on multi-class problems with a relatively large number of labels. The results are shown in Figure 3. Figure 4 shows the SVM model hyperparameter search process using GridSearchCV with a stratified cross-validation scheme, which is used to determine the best model configuration before the evaluation stage.

```
Menjalankan GridSearch untuk SVM...
Fitting 5 folds for each of 80 candidates, totalling 400 fits
GridSearch SVM selesai dalam 261.82 detik
```

Figure 3. GridSearchCV Process for SVM Single-Label Classification

```
CV Score (F1) terbaik: 0.44732610336591005
Kombinasi model terbaik: Pipeline(steps=[('scaler', MinMaxScaler()),
                ('feat_select', SelectPercentile(percentile=70)),
                ('clf', SVC(C=1, class_weight='balanced', gamma=1))])

Skor Test (akurasi) SVM: 0.6015625
```

Figure 4. Best Hyperparameter Configuration and Performance of the SVM

The results of the evaluation showed that the SVM model achieved a macro value of F1-score of 0.447 in the cross-validation process. In the test data, the model yielded an accuracy of 0.60, indicating that about 60% of the test data was correctly classified into appropriate learning style profiles. The macro F1-score (0.49) and weighted F1-score (0.61) in the test data showed a gap in performance between classes, especially between classes with large data sizes and minority classes. The results of the evaluation are shown in Figure 4.

To provide an overview of the model's prediction patterns, the performance of single-label classification using the SVM was further analyzed through a confusion matrix. This visualization shows the comparison between the actual labels and the predicted results labels on the test data, thus allowing the identification of correct prediction patterns as well as misclassification between FSLSM learning style profiles. The correlation matrix is shown in Figure 5.

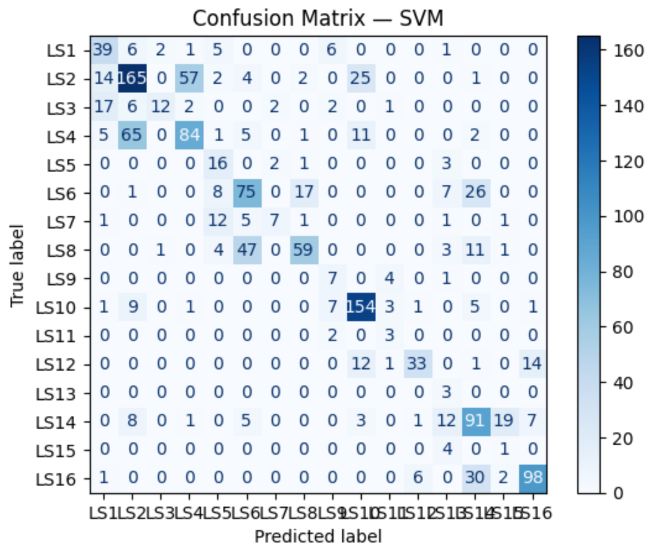

Figure 5. Confusion matrix SVM

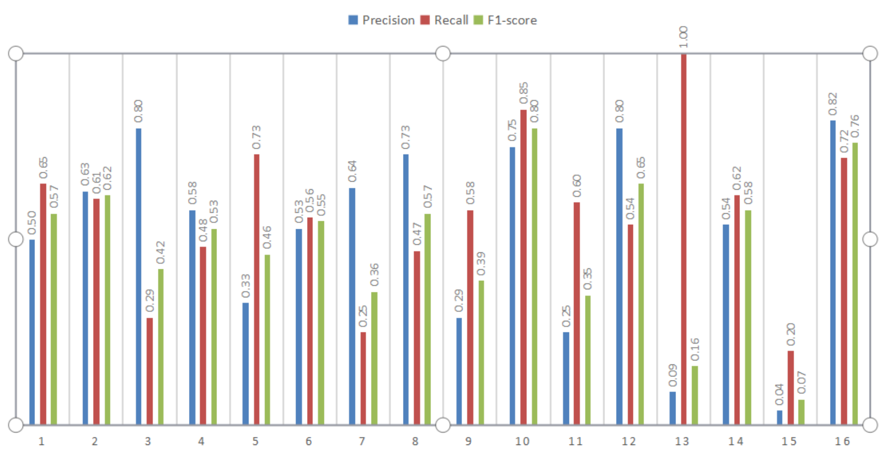

Figure 6. SVM classification report

Figure 6 illustrates the performance of the Support Vector Machine (SVM) model in single-label learning style classification across all learning style classes. The results indicate that SVM achieves relatively stable precision and recall for several learning style categories, such as LS-2, LS-6, and LS-16, which are characterized by more dominant behavioral patterns and sufficient data representation. In contrast, noticeable variations in F1-score are observed for certain classes, including LS-13 and LS-15, suggesting inconsistent predictive performance for learning styles with smaller sample sizes or more complex behavioral characteristics. These findings indicate that while SVM is effective in separating some learning style classes, it is less robust in capturing inter-class overlap and non-linear relationships inherent in LMS behavioral data, thereby serving more appropriately as a baseline model for learning style classification.

Although the SVM model demonstrates reasonable performance in classifying several learning style categories, the variability observed across classes indicates limitations in capturing complex and non-linear behavioral patterns present in LMS data. To further investigate whether a more flexible and ensemble-based approach can improve classification robustness and consistency, the next experiment evaluates the performance of the Gradient Boosting classifier.

4.2 Experiment 2 : Gradient Boosting (GB) Singgle Label Classification

To obtain the optimal configuration of the Gradient Boosting model in single-label classification, a hyperparameter optimization process was carried out using GridSearchCV with a Stratified K-Fold Cross-Validation scheme (k = 5). This stage aims to evaluate various combinations of learning parameters to improve the model's ability to predict the FSLSM learning style profile more accurately and stably. The results of this process can be seen in Figure 7.

```
Menjalankan GridSearch untuk Gradient Boosting...
Fitting 5 folds for each of 120 candidates, totalling 600 fits
GridSearch GBT selesai dalam 2328.45 detik
```

Figure 7. Hyperparameter Optimization Process of the Gradient Boosting Model Using GridSearchCV

Figure 4.8 shows that the GridSearchCV process on the Gradient Boosting model involves evaluating 120 parameter combinations on each validation fold, resulting in a total of 600 model trainings. The relatively long computation time, which is about 2328 seconds, reflects the complexity of the Gradient Boosting model, especially due to the influence of the number of estimators, learning rate, and tree depth on the learning process. The best configuration obtained from this stage is further used in the evaluation of the model's performance on the test data.

To evaluate the performance of the Gradient Boosting model in the single-label classification scheme, a validation process was carried out using cross-validation and testing on test data. This evaluation aims to measure the stability of the model during training as well as the model's generalization ability against previously unseen data. The results of the performance evaluation of the Gradient Boosting model are shown in Figure 8.

```
CV Score (F1) terbaik: 0.7850409242462336
Kombinasi model terbaik: Pipeline(steps=[('feat_select', SelectPercentile(percentile=70)),
                ('clf', GradientBoostingClassifier(random_state=0))])
Skor Test (akurasi) GBT: 0.8423295454545454
```

Figure 8. Cross-Validation and Test Performance of Gradient Boosting Classifier

Based on Figure 8, the Gradient Boosting model demonstrates strong performance, achieving a cross-validation F1-score of 0.7850, which indicates a good balance between precision and recall. The application of SelectPercentile with 70% of the features effectively reduces irrelevant attributes and enhances model performance. Furthermore, the model attains an accuracy of 0.8423 on the test data, reflecting good generalization ability. The relatively small difference between the cross-validation and test results suggests that the model does not suffer from significant overfitting, confirming Gradient Boosting as a reliable approach for single-label learning style classification using LMS behavioral data.

To gain a deeper understanding of the performance of the Gradient Boosting model in each class, the evaluation was continued using a confusion matrix. This visualization allows for a detailed analysis of the distribution of true and false predictions on each learning style label, so it doesn't rely solely on aggregate metrics such as accuracy or F1-score. The results of the confusion matrix for the Gradient Boosting model are shown in Figure 9.

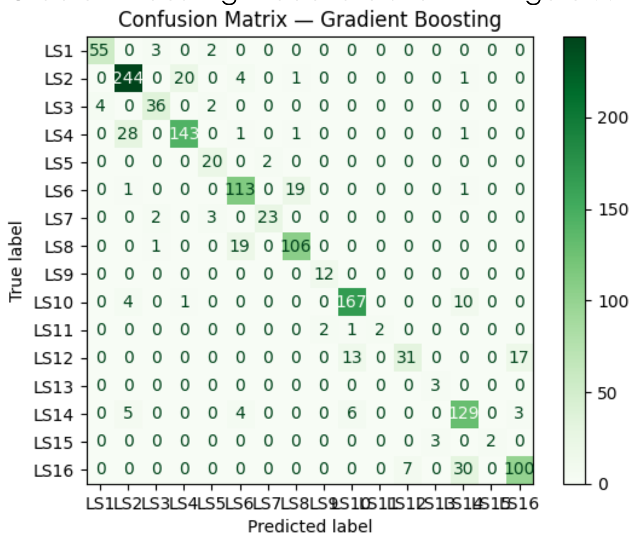

Figure 9. Confusion Matrix Results of Gradient Boosting

Based on Figure 9, the confusion matrix shows that the Gradient Boosting model achieves good classification performance, as indicated by the dominance of values along the main diagonal. Several labels, including LS4, LS6, LS8, LS10, and LS14, exhibit high true positive rates with relatively low misclassification, suggesting that their behavioral patterns are well captured by the model. Notably, LS2 achieves a very high number of true positives, indicating that the model consistently and accurately learns this learning style, likely due to its larger sample size. Despite the strong performance on LS2, a small number of misclassifications to behaviorally similar labels remain, reflecting overlapping characteristics in LMS behavioral data and the inherent limitations of a single-label classification approach. Overall, the confusion matrix confirms that the Gradient Boosting model provides stable and consistent predictions with adequate generalization capability, supporting its suitability for single-label LMS-based learning style classification.

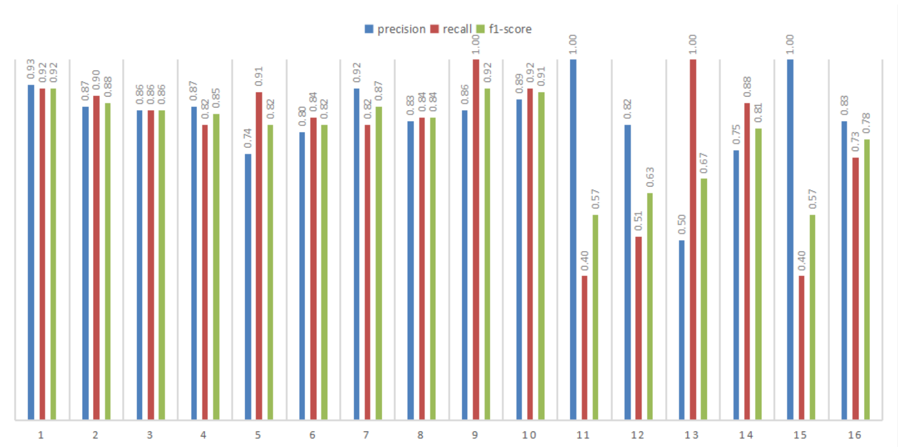

Figure 10. Gradient Boosting single label classification report

Figure 10 presents the per-class classification performance of the Gradient Boosting model for single-label learning style classification. Overall, the model demonstrates consistently high precision, recall, and F1-score across most learning style classes, indicating a strong and balanced predictive capability. Compared to the SVM results, the performance distribution across classes appears more stable, suggesting that Gradient Boosting is more effective in capturing complex and non-linear patterns in LMS behavioral data.

Several learning style classes, including LS2, LS4, LS6, LS8, LS10, and LS16, achieve high and well-balanced evaluation metrics, reflecting that their behavioral characteristics are clearly represented and can be learned effectively by the model. In contrast, a small number of classes, such as LS11, LS13, and LS15, exhibit relatively lower recall or F1-score values, which can be attributed to limited sample sizes and overlapping behavioral patterns with other classes. This phenomenon highlights the inherent challenge of distinguishing learning styles that share similar interaction profiles within a single-label classification framework.

Overall, the results confirm that the Gradient Boosting model provides more robust and consistent classification performance across learning style categories than baseline approaches. Its ability to maintain balanced precision and recall across most classes supports its suitability for LMS-based learning style detection and reinforces its effectiveness as the preferred model in this single-label classification experiment.

4.3 Performance Comparison of SVM and Gradient Boosting

To evaluate and compare the effectiveness of the classification algorithm used in the single-label learning style detection scheme, a comparative analysis was conducted between SVM and GB. This comparison is based on aggregate evaluation metrics that include accuracy, precision, recall, and F1-score, and considers the stability of the model's performance in dealing with unbalanced class distributions. A summary of the performance comparison results of the two models is presented in Table 4.

Table 4. Performance comparison result of the SVM and GB

Aspect	Support Vector Machine (SVM)	Gradient Boosting
Accuracy	0.6	0.84
Precision (Weighted Avg)	0.64	0.85
Recall (Weighted Avg)	0.6	0.84
F1-score (Weighted Avg)	0.61	0.84
Macro F1-score	0.49	0.79
Performance on Majority Classes	Moderate	Very Good
Performance on Minority Classes	Poor to Moderate	More Stable
Robustness to Class Imbalance	Low	High
Confusion Matrix Pattern	Dispersed errors across classes	Dominant diagonal (high TP)
Model Complexity	Medium	High (ensemble-based)

Table 5 presents a comparative evaluation of the Support Vector Machine (SVM) and Gradient Boosting (GB) models for single-label learning style classification based on precision, recall, F1-score, and support across all learning style (LS) profiles. Overall, the results clearly indicate that the Gradient Boosting model consistently outperforms SVM across most evaluation metrics and learning style classes.

In terms of overall performance, Gradient Boosting achieves a substantially higher accuracy (0.84) compared to SVM (0.60). This improvement is further reflected in the macro-averaged F1-score, which increases from 0.49 (SVM) to 0.79 (GB). The large gap in macro-average performance highlights the superior ability of Gradient Boosting to handle class imbalance and maintain balanced performance across both majority and minority learning style classes. Similarly, the weighted F1-score improves from 0.61 to 0.84, confirming that the performance gain is consistent when class frequencies are taken into account.

At the class-level analysis, Gradient Boosting demonstrates marked improvements in recall and F1-score for most learning style profiles. Classes with moderate to large sample sizes, such as LS-2, LS-4, LS-6, LS-8, LS-10, LS-14, and LS-16, show high and well-balanced precision–recall values under the GB model, indicating that their LMS behavioral patterns are effectively captured. In contrast, SVM exhibits unstable recall values for several classes (e.g., LS-3, LS-7, LS-11, and LS-15), which results in low F1-scores despite occasionally high precision.

For minority classes with very limited support, such as LS-11, LS-13, and LS-15, both models experience performance degradation; however, Gradient Boosting still achieves noticeably higher F1-scores than SVM. This suggests that the ensemble-based nature of Gradient Boosting provides better robustness in learning discriminative patterns from sparse data compared to the margin-based decision boundaries of SVM.

Table 5. Performance Comparison of SVM and Gradient Boosting for Single-Label Learning Style Classification

LS Profile	Precision		Recall		F1 Score		Support
	SVM	GB	SVM	GB	SVM	GB	
LS-1	0.50	0.93	0.65	0.92	0.57	0.92	60
LS-2	0.73	0.87	0.61	0.90	0.62	0.88	270
LS-3	0.80	0.86	0.29	0.86	0.42	0.86	42
LS-4	0.58	0.87	0.48	0.82	0.53	0.85	174
LS-5	0.33	0.74	0.73	0.91	0.46	0.82	22
LS-6	0.53	0.80	0.56	0.84	0.55	0.82	134
LS-7	0.64	0.92	0.25	0.82	0.36	0.87	28
LS-8	0.73	0.83	0.47	0.84	0.57	0.84	126
LS-9	0.29	0.86	0.58	1.00	0.39	0.92	12
LS-10	0.75	0.89	0.85	0.92	0.80	0.91	182
LS-11	0.25	1.00	0.60	0.40	0.35	0.57	5
LS-12	0.80	0.82	0.54	0.51	0.65	0.63	61
LS-13	0.09	0.50	1.00	1.00	0.16	0.67	3
LS-14	0.54	0.75	0.62	0.88	0.58	0.81	147
LS-15	0.04	1.00	0.20	0.40	0.07	0.57	5
LS-16	0.82	0.83	0.72	0.73	0.76	0.78	137
Accuracy	-		-		0.60	0.84	1408
Macro avg	0.52		0.57		0.49	0.79	1408
Wighted avg	0.64		0.60		0.61	0.84	1408

These results indicate that while SVM can serve as a baseline classifier for learning style prediction, its performance is sensitive to class imbalance and overlapping behavioral patterns. Conversely, Gradient Boosting demonstrates stronger generalization capability, higher stability across learning style profiles, and better handling of non-linear relationships inherent in LMS behavioral data. Consequently, Gradient Boosting is more suitable for single-label learning style classification in LMS-based learning analytics applications.

5.0 CONCLUSION

This study proposed a machine learning-based approach for automatic learning style classification using LMS behavioral data grounded in the Felder–Silverman Learning Style Model (FSLSM). Using LMS activity logs collected from Universitas Siber Asia over three academic years, the results demonstrate that learning styles can be inferred effectively from observable learner behaviors without relying on subjective questionnaires. Experimental findings show that Gradient Boosting consistently outperforms Support Vector Machine in single-label learning style classification, achieving higher accuracy and macro F1-score, as well as more stable performance across learning style profiles. These results indicate that ensemble-based methods are more robust in modeling complex and non-linear behavioral patterns inherent in LMS data, particularly under imbalanced class distributions. While SVM can serve as a baseline model, its performance is less stable for minority learning style classes. Overall, this study confirms the potential of LMS behavioral logs combined with optimized machine learning techniques for automatic FSLSM-based learning style detection, supporting the development of data-driven adaptive learning systems. Future work will extend this framework to multi-label classification and evaluate its integration into real-time LMS environments.

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