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Machine Learning-Based Identification and Behavioral Analysis of Student Learning Styles in Online Learning Environments Using FSLSM and Clustering Techniques

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Abstract

A major objective of the systematic education process is lifelong learning. Monitoring and identification of the learning styles of the learners in delivering educational content plays a significant role for improving both teaching and learning aspects. In E-learning environment, identification of the learning style plays a pivotal role as it highly impacts the module content design process for the online learning environment to improve the knowledge of the students in a precise manner. When it is considered the Moodle learning platform, a popular method used for learning style identification is considering the access frequency. But considering only the access frequency will always not predict the correct results as there may be situations where students access the course material online but do not spend sufficient time with educational materials. The proposed

methodology is a novel improved approach which considers both access frequency and the time spent on the learning material by applying the K-Means Clustering. In this research, Felder Silverman learning Style model (FSLSM) which is an acceptable learning style identification methodology was used as the leaning model. For the data collection process, it has been used the Moodle logs for the getting the access frequency and a deigned reusable Moodle plugin for measuring the total time spent on the activities. Then K- Means clustering was applied, which is an unsupervised machine learning algorithm to identify the learning style of the learners. The development of an application that employs these models to dynamically identify and predict student learning styles adds practical value, enabling integration into learning management systems. Finally, the research introduces a temporal analysis of learning behavior transitions, understanding of how student engagement evolves over time.

Keywords: FSLSM; Machine Learning; Clustering; Learning Styles

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1. Introduction

Human existence is not complete without learning, which can be influenced in both informal and systematic ways [1]. Learning is a process that allows people to increase their knowledge and skills so they can complete a task or activity more successfully [2] It involves learning new information via a variety of techniques, including education, practice, experimentation, and observation. The rapid development of technologies has made a drastic evolution to learning environment [3] Rather than delivering knowledge in the conventional classrooms. Education has improved by receiving educational content through online learning platforms [4] [5]. But when creating the course content in the online learning environment, as well as delivering the course contents, it is required to monitor the success of the learning process. When creating courses for online learning environments, it is important to take students' various learning preferences into account. The phrase "learning style" describes a number of methods that people utilize when learning something new, such as visual learners who prefer pictures to words or auditory learners who prefer verbal instructions to written ones. Otherwise, the instructors will not be able to measure whether the content is delivered as expected successfully (Khaira, 2017). In general, it's critical to acknowledge the significance and worth of knowing each person's particular learning style. So that proper help may be given to them throughout their educational path. This will allow teachers to provide everyone, irrespective of the sort of learner they may be, with the tools they need to achieve academically [7] The intension of this research is to identify the learning style of the students using improved methodology using the machine learning techniques. For this, Felder Silverman Learning style model was used as the respective learning style model. The novelty of this model is that rather than considering the access frequency, time spent on course activities identify learning styles, which has been less explored in previous studies.

This paper has been organized as follows; section I gives an Introduction to the research. Section II presents details about the background phenomena of the learning style identification and the using machine learning for learning style identification process. As well as the significance of conducting this research, the II section depicts the details about the related works. The section discussed the methodological approach used in the research for data collection and identification of learning style by using the classification. Section V discusses the results gained through the research, the evaluation matrices for evaluation of the model and the last section presents information about the conclusion of the chapter.

2. Background

2.1. Learning Environment and Learning Styles

The rapid advancement of Information Technology has changed the traditional way of learning in the classroom-based environment. Instead, the digitization of the technologies has made the learning environment to online based experience from the recent years (Shaheen Parveen & Shaikh Imran Ramzan, 2024), [9] Either traditional classroom based on novel online/ distance based learning infrastructure, a key requirement is to measure the student's success rate or the performance [10]. Students have various styles of their own learning, for a lifelong learning process, the best way is to explore the learning resources as per own way of learning rather than just access the learning materials or sources in a way that teachers provided [11]. Each student's unique set of knowledge, experiences, and abilities informs their learning process. Learners' goals can be more precisely met with the aid of personalized learning models. Finding out how each student learns best is crucial in personalized education. Several learning style models are used to make this determination, including the NASSP Model, the Theory of Multiple Intelligences by Howard Gardner, the VARK Model created by Neli Fleming, the Felder-Silverman Learning Styles Model, the David Kolb Model, the Peter Honey and Alan Mumford Model, and others [12].

2.2. Research Problem

With the rise of technological advancements, virtual education has become more accessible than ever, prompting researchers to explore the most effective ways to instruct online courses and customize each student's learning experience. More research in this field is becoming more and more necessary so that teachers may learn how to properly teach online courses while still giving each student individualized attention. The theoretical challenges involved in analyzing generic logs of Moodle and assessing course activity to determine a student's learning style are quite complex. Students might have access to study resources, for example, without retaining any particular biases or preferences. This suggests that only keeping track of log entries once could not fully represent their preferences, making it challenging to evaluate their learning styles using this information alone.

Researchers should extend their focus beyond just the accessibility features in Moodle logs. They need to analyze how much time students spend on specific activities and whether they revisit the same content multiple times within the online platform. Such studies, as suggested by FSLSM, can yield valuable insights into the types of resources students prefer when engaging in online materials. This information can then inform teaching strategies tailored to meet the specific needs and interests of learners.

For the identification of the learning style, many of the conventional learning style identification methodologies are in practice such as FSLSM and Kolb's Learning. If consider the FSLSM methodology it also uses conventional Indexed Learning Style method. But, with the rapid development of technologies in the education field as E learning, applying these conventional methods will not always be a success for identifying the learning Styles. To identify leaning style in dynamic leaning Environment, it required new technology adopted methods. In this scenario, Machine Learning plays a significant role. Machine learning techniques are capable of make predictions based on supervised or unsupervised learning algorithms rather than using the conventional manual paper-based methods for identification of the learning styles.

2.3. The Felder Silverman Learning Style Model (FSLSM)

The Felder-Silverman Learning Style Model (FSLSM) was developed by Dr. Richard M. Felder and Dr. Linda K. Silverman in the 1980s, primarily to address the diverse learning preferences of engineering students. This model is based on the premise that individuals have unique ways of processing information and learning, which can significantly impact their educational experiences. The FSLSM is recognized as one of the most adopted learning style models in the context of educational technology and quality improvement processes. Research [13] highlights that understanding learners' preferences can significantly enhance the effectiveness of e-learning systems and personalized learning experiences. The Felder-Silverman learning style model (FSLSM) uses values on four dimensions to characterize learners as Active/Reflective, Visual/Verbal, Sensing/Intuitive, Sequential/Global.

3. Related Works

The study [14] explored the use of Moodle logs and machine learning techniques to identify students' learning styles within an online learning environment. Courses were evaluated based on three levels of completion: 40%, 60%, and 80%. Key factors analyzed included forum posts, quiz access, and conversation logs.

Another experiment [15] involved 35 students enrolled in a computer science module, utilizing the Moodle LMS for their data structure course, which was developed using the FSLSM model and Moodle logs. The system tracked all student activities, enabling the extraction of various features at any point during or after the course. The research examined the application of machine learning classification techniques to identify students' learning styles, utilizing the FSLSM model and Moodle logs as attributes. Among the various methods tested, achieving an accuracy rating of 45.55% [16] the Support Vector Machine (SVM) demonstrated the highest accuracy in predicting learners' dominant intelligence

This study [17] introduces a novel approach for evaluating learners' automatic and dynamic learning styles, drawing on existing literature. The approach creates learning style insights that may be used as labels in datasets by combining student behavior data from the LMS with the ILS questionnaire. The Decision Tree, Naive Bayes, and K-Nearest Neighbor classification algorithms were examined. These models were assessed using the sklearn library in Python using two techniques: 10-fold cross-validation and an 80:20 train-test split. Another study (Ikawati et al., 2020) focused on identifying students' learning styles within the Moodle learning environment, utilizing Moodle logs as attributes. The research sample consisted of 65 students. For data classification, the study employed Decision Tree and Ensemble Learning as machine learning algorithms. The research (Ikawati et al., 2020) reveals that Moodle logs are the main criterion used in this study to determine the learning preferences of students in the Moodle learning environment. The sample population for the research study consists of 65 students in total. To classify the data, the researchers used the ensemble learning technique and the Decision Tree algorithm. According to the results, the Decision tree model has a 92% accuracy rate whereas the Gradient Boosted Tree model has an 88% accuracy rate. According to the literature review conducted, analyzing the students learning styles and using machine learning approaches to analyze the learning style in the education field is highly in practice. But using both access frequency as well as time spent on activities are still less explored..

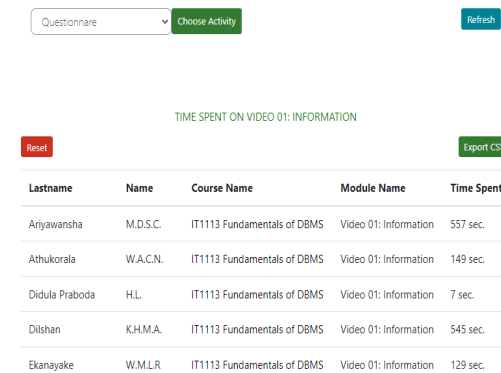
4. Methodology

This section of the research discusses the methodological approach used for conducting the research.

4.1. Significance of the Research

One of the main contributions of research to determining students' learning styles is this. The Moodle platform has tools for tracking how long it takes to finish tasks and assignments, but it lacks a system for monitoring how much time a user spends on all of the activities that are pertinent to the course module. A unique new time-counting plugin was created for this. Below figure 01 is a screen grab of the user interface.

Time Spent: IT1113 Fundamentals of DBMS



Lastname	Name	Course Name	Module Name	Time Spent
Ariyawansa	M.D.S.C.	IT1113 Fundamentals of DBMS	Video 01: Information	557 sec.
Athukorala	W.A.C.N.	IT1113 Fundamentals of DBMS	Video 01: Information	149 sec.
Didula Praboda	H.L.	IT1113 Fundamentals of DBMS	Video 01: Information	7 sec.
Dilshan	K.H.M.A.	IT1113 Fundamentals of DBMS	Video 01: Information	545 sec.
Ekanayake	W.M.L.R.	IT1113 Fundamentals of DBMS	Video 01: Information	129 sec.

Figure 1: Time Monitoring Plugin

Every course activity page has the plugin installed, which tracks how much time a user spends on each activity by using JavaScript libraries. A PHP query is used to access the recorded time, which is kept in the Moodle database. The Moodle plugin makes it simple to track how much time a particular student spends on an activity because each user is assigned a unique ID. The time is transformed to seconds after being measured in milliseconds. Instructors and course administrators with privileged access can view and download time-spent statistics in CSV format. Students are unable to access the collected data.

4.2. Indexed Learning Style Questionnaire Plugin

As illustrated in Figure 02, An ILS plugin was created for Moodle that can be used again. This is available to the students, who can use it to fill out the ILS questionnaire. According to the FSLSM[20], the ILS questionnaire is already recognized as a tool for determining a student's learning style. There are forty-four questions in all, with eleven questions for each dimension. The traditional ILS questionnaire has been transformed into a computerized format in this plugin, and the replies were utilized for the labeling process during dataset construction.

View Reports

1. I understand something better after I

☐ A. try it out.

☐ B. think it through.

2. I would rather be considered

☐ A. realistic.

☐ B. innovative.

Figure 2: Indexed learning style plugin

4.3. Course Designing in Moodle

it was designed in order to analyze how students behaved in online learning environments using the FSLSM parameters. Each course's course materials were included during the course design process, as seen in the schematic in figure 03, According to the FSLSM's rule classifications, it was utilized in forum posts, exercises, movies, charts, photos, graphs, notes, theoretical concepts, and conceptual maps.

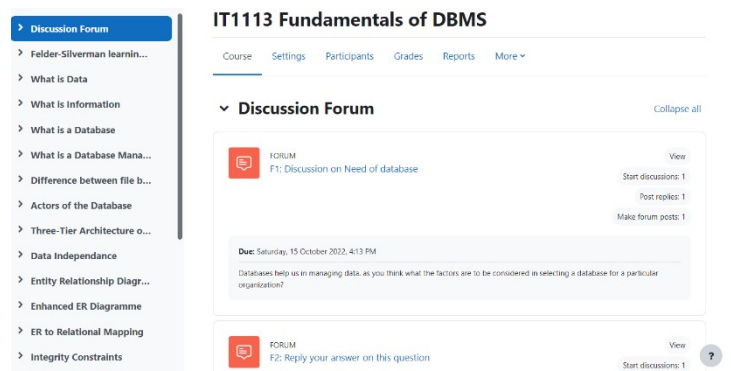


Figure 3: Course Design

4.4. Overall Methodology

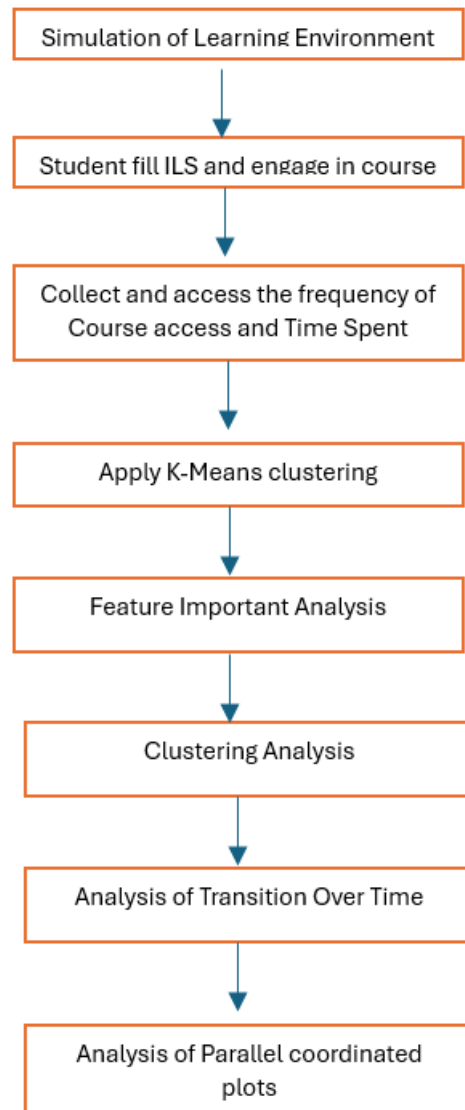


Figure 4: Overall Methodology

As shown in figure 4, overall methodology, as the first step, the students are allowed to engage in the course modules. Then the students are allowed to engage in the activities as per their preferences. Considering each dimension of the FSLSM, it was designed respective accepted activities in Moodle like Forum Posts to measure Active and Reflective dimensions. Concepts building and conceptual mapping for Sensing and Intuitive, Accessing Videos and Audios for Visual and Verble, Linear and non-liner behavior of access for sequential and global dimensions .Once the course modules are completed within the particular time period when the allocated time period is over, the access frequency data is taken from the Moodle logs and the total time spent on the activities are tracked using the plugin developed. Then the K-Means clustering was applied using the entire normalized feature set with K=4 as there are four main dimensions. Then feature importance analysis was analyzed to measure how important each feature is in a dataset when predicting a target variable(Ewald et al., 2020.) ,[22] Furthermore the Learning style transition over time was considered for model dimensional analysis.

4.5. Data set

For the experiment, 150 students asked for the data sample and allocated 50 hours to work with the Moodle platform. Then the records were obtained after completion of the course modules. Then it was applied the K Means clustering. In this process the data set was split into training (80%) and testing (20%) sets.

5. Results and Discussion

5.1. Results of Feature Importance Analysis

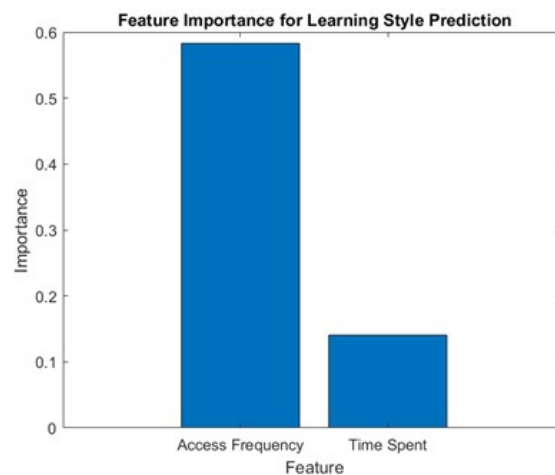


Figure 5: Feature Importance Analysis

As the results show in figure 5 the feature importance chart indicates that "Access Frequency" is significantly more important than "Time Spent" for predicting learning styles. This suggests that how often a user accesses the material is a key factor in determining their learning style. Depends on the results The model's performance can be considered effective if it achieves good scores on the above metrics, indicating well-separated and cohesive clusters. Adjusting the model to emphasize "Access Frequency" could potentially enhance clustering quality.

5.2. Results of Clustering Analysis

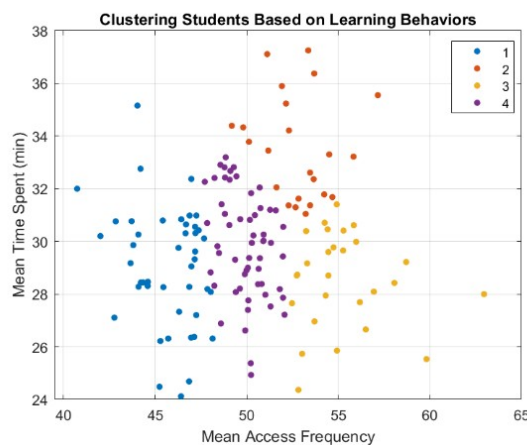


Figure 6: Clustering Analysis

The scatter plot in figure 6 illustrates the clustering of students based on two features: Mean Access Frequency and Mean Time Spent. Here are some insights from the clustering result,

Cluster 01 (Blue):

- Characteristics: Students in this cluster have lower access frequency and spend less time on average.
- Interpretation: These students might be less engaged or prefer concise study sessions.

Cluster 02 (Orange):

- Characteristics: This group shows higher time spent with moderate access frequency.
- Interpretation: These students might prefer fewer but longer study sessions, indicating a deep learning approach.

Cluster 03 (Yellow)

- Characteristics: Students here have high access frequency but spend less time per session.
- Interpretation: This could indicate a preference for frequent, short study sessions, possibly reflecting a surface learning style.

Cluster 04 (Purple):

- Characteristics: This cluster is characterized by moderate access frequency and time spent.
- Interpretation: These students might have a balanced approach, neither too frequent nor too lengthy in their study habits.

When it considers the model performance The clusters appear distinct, suggesting that the model effectively differentiates between different learning behaviors in Separation and Cohesion and the use of "Access Frequency" and "Time Spent" as features seems appropriate, as they provide clear distinctions between student groups in resource allocation. Overall, the clustering model provides valuable insights into student learning behaviors, enabling more personalized and effective educational strategies

5.3. Transition Over Time



Figure 7: Transition Over Time

Figure 07 shows the transition over time.

Cluster 01 (Blue):

- Trend: Generally lower access frequency compared to other clusters.
- Insight: This cluster might represent students with consistent but lower engagement levels. They could benefit from strategies to increase their interaction with learning materials.

Cluster 02 (Orange):

- Trend: Shows moderate fluctuations with occasional peaks.
- Insight: These students might have variable engagement, possibly influenced by external factors like exams or project deadlines

Cluster 03(Yellow)

- Trend: Exhibits the highest variability and frequent peaks.
- Insight: This cluster could represent students who engage intensely at certain times, possibly indicating cramming behavior or response to specific academic demands.

Cluster 04 (Purple):

- Trend: Moderate and stable access frequency.
- Insight: These students maintain a balanced approach, suggesting consistent study habits.

The Temporal patterns reveal that the model effectively captures temporal variations in student behavior, highlighting different engagement patterns over time. As well as the resource planning show that the distinct trends suggest that the model successfully differentiates between various learning styles, providing actionable insights for educational interventions. As the educational implications, Educators can use these insights to provide tailored support. For example, students in Cluster 1 might need motivation strategies, while those in Cluster 3 could benefit from time management workshops in targeted support. For the resource planning understanding these patterns helps in planning resources and support services to align with peak engagement periods.

5.4. Results of Parallel Coordinated Plots

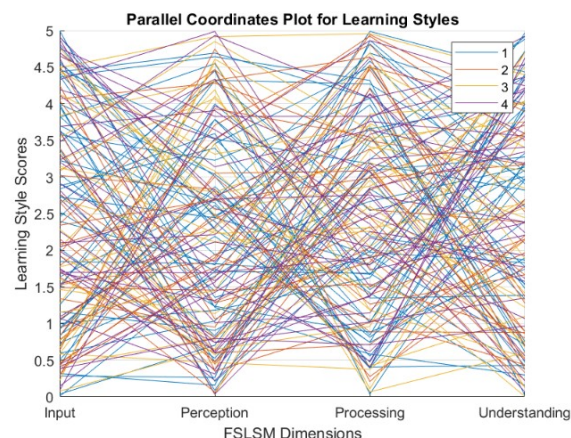


Figure 8: Results of Parallel Coordinated Plots

The plot in figure 08 represents learning style scores across different FSLSM (Felder-Silverman Learning Style Model) dimensions: Input, Perception, Processing, and Understanding. Each line represents an individual or group score, color-coded based on categories (1 to 4). When it is discussed about the model behavior High variability is observed across the FSLSM dimensions, which indicates diverse learning styles among the data points. There appears to be no dominant trend across dimensions, as the lines crisscross extensively, suggesting high diversity in responses. And also, this gives an insight of the clustering as groups are not well-separated in the feature space, which could signal the need for improved feature engineering or model refinement. Regarding the outliers The plot has lines that significantly deviate from the general pattern (lines jumping from extremes, such as from 0.5 to 4.5 between dimensions). These could represent outliers or noise in the dataset.

6. Conclusion

As the conclusion, in the process of prediction of the learning styles K-means clustering model has performed in a precise manner, the Felder Silverman Learning Style model is one of the best model for identification of the learning with descriptive dimensions in online learning environment as well This methodology enables the identification of comprehensive learning profiles based on real LMS interaction data using unsupervised learning. Unlike traditional FSLSM profiling, this approach captures dynamic, behavioral learning styles that evolve over time, providing actionable insights for personalized learning design. The Feature importance analysis reveals that access frequency is a primary determinant in clustering learners based on their learning styles. The clustering results indicate that the model successfully separates distinct learning behaviors, demonstrating strong cohesion within groups. 'Access Frequency' and 'Time Spent' were effective features for distinguishing learner engagement patterns. Temporal analysis indicates that the model successfully tracks changes in student engagement over time. These evolving patterns, along with resource planning insights, underscore the model's ability to distinguish learning styles and support informed instructional strategies. The parallel coordinate plot illustrates significant variability across the FSLSM dimensions Input, Perception, Processing, and Understanding indicating a diverse range of learning styles among students.

One of the research projects conducted by author previously [23] concerned on the applying supervise classification algorithms for identification of the learning style. In this research it has been conducted an extension of applying K-means clustering for identification of the learning styles. So, the proposed methodology for identifying the learning style performed well with the K-means clustering.

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