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Integrated Model for Identifying the Learning Style of the Students Using Machine Learning Techniques: An Approach of Felder Silverman Learning Style Model (FSLSM)

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Abstract-*Identifying students' learning behaviours in learning environments is an essential factor in the success of the lifelong learning process. The intention of the research is to propose a methodology for identifying the learning style of the students in the online learning environment using machine learning techniques. The Felder Silverman learning style model (FSLSM) was used as the learning style identification model, and Moodle was used as the online learning platform. Data was collected for two modules that each module consisting of 150 students who are following BSc, Information Technology Degree of General Sir John Kotelawala Defence University. Once the students enrolled on the courses, their behaviours in the online learning environment were tracked using Moodle logs and the time spent on each activity according to the FSLSM and applied machine. Then the machine learning classification techniques such as Decision Tree, Logistic Regression, Random Forest, Support Vector Machine, and K-Nearest Neighbors were applied to train the several models covering each main four dimensions of the FSLSM. The results show that each dimension of the FSLSM Decision Tree Classifier performed well with an accuracy of 95% for Input,80% for Perception, 90% for Processing and 95% for Understanding, dimensions. The models were evaluated using k-fold cross-validation and Grid search methods and Hyper Parameter Tuning was done accordingly. Moreover, the validity of the models was evaluated by considering the Mean Squared Error (MSE), BIAS and the values of the variance.*

Keywords- Machine Learning, FSLSM, Learning Style

I. INTRODUCTION

E-learning or online learning has become an increasingly popular part of the instructional process in educational institutions, especially universities. This is largely due to globalization and its effects on government, business and the spread of ideas around the world(Suresh Babu & Sridevi, 2018). With e-learning being so widely available, schools can provide distance learning education across cultural and geographical boundaries. In addition to this convenience factor for students, there are also a number of different platforms available for use by educators worldwide – from free licensed systems such as Ganesha or Claroline, Moodle to proprietary licensed platforms like MyTeacher or E-doco (Ouadoud et al., 2021).

Learning is an essential human activity that can be shaped and developed in both informal and systematic ways. Research has shown that learning styles vary from person to person, which makes it important for educators to understand how each individual learns best. This understanding helps them design courses and content that are tailored to the needs of their students, providing them with a more effective and adaptive teaching experience.

The term "learning style" refers generally to the different approaches people take when engaging in educational activities such as reading or studying material provided by instructors or mentors. The concept of learning styles has been met with a largely positive reception by the public(Shemshack & Spector, 2020). The learning process is individualized, as it is shaped by the learners' unique interactions, abilities, and experiences. Personalized learning models enable learners to accomplish their goals more precisely. The most essential task in personalized learning is identifying the learning style of each individual student. Various learning style models are used to determine the learning style. There are various learning style models use to identify the learning style as Peter Honey and Alan Mumford's Model, David Kolb's model, VARK model by Neli Fleming's NASSP model Anthony Gregrorc's model, Gardner's Theory of multiple intelligence and Felder-Silverman Learning Style Model (Rasheed & Wahid, 2021)

Therefore, the purpose of this study is to propose an improved model for the identification of students' learning styles in an online learning environment. The research is designed on the identification of the student's learning styles using the Felder-Silverman Learning Style Model (FSLSM), one of the most widely accepted models for learning style identification (Essi Essi Kanninen, 2009),(Bishouty et al., 2019),(Herman Dwi, 2014), (Revathi Sagadavan & Shiney John, 2019), (Zine et al., 2019). Moodle was used as an online learning platform to provide students with a learning environment and to monitor data. According to the FSLSM, two courses were designed for the students in Moodle, and the course content was developed based on identifying the student's learning styles. Most research in this field has focused on identifying students' learning styles using Moodle logs. The proposed model consisted of an integrated model that utilized both Moodle logs to get the access frequency and the amount of time spent on each designed activity. Then, machine learning classification algorithms were used to analyse the data and determine the learning styles of the students, as well as the patterns for constructing machine learning models.

II. BACKGROUND

In recent years, research studies have focused on identifying the learning styles of students in an online learning environment(Zapalska & Brozik, 2006), (Doulik et al., 2017), (Dağ & Geçer, 2009)Through these studies, researchers are attempting to understand how different types of learners best absorb information and what strategies can be used to ensure their success in courses taken through this medium. By understanding which methods work best for each student's individual needs, teachers will be able to better tailor instruction according to those preferences and strengths. The results from such research could provide valuable insight into how classes should be taught online and which tools or methods would prove most effective for each learner's unique set of abilities. Additionally, it could also create a more personalized educational experience by allowing instructors the opportunity to customize instruction based on the particular needs of their students rather than relying solely on traditional teaching techniques that may not always meet everyone's requirements.

A. Research Problem

.Since technological developments have made virtual education more accessible than ever before, studying how best to teach online classes and personalize the educational experience for each individual student is of the highest priority. Therefore, more study is required in this area so that teachers can better understand how to approach teaching online courses while still giving each student the individual attention they deserve.

The theoretical issues behind the methodologies of considering generic Moodle logs and accessing course activities for determining a student's learning style are complex. For example, students may access study reference material without necessarily having any particular preference or leaning towards that material. This means that tracking these log hits only single occurrence may not be an accurate reflection of their actual preferences and thus their learning styles cannot be accurately determined from this data alone.

To gain more insight into student preferences, researchers should look beyond just accessibility features in Moodle logs; they should also consider how much time a student spends on certain activities as well as if they return multiple times to the same activity or content area within the online environment. According to FSLSM this type of analysis can provide valuable information about what kind of resources students prefer when engaging with online materials which can then help inform decisions regarding teaching strategies tailored specifically for those learners' needs and interests.

Therefore, proposing a model by considering both frequencies of accessing the course contents as well as the time spent on each activity will provide more descriptive insight into learning style identification. The proposed model suggests and works with more descriptive parameters as the frequency of accessing the course contents and considering the time value spent on the activities.

B. Felder Silverman Leaning Style model (FSLSM)

Felder and Silverman's Learning Style Model (FSLSM) is a widely used model for understanding the learning styles of students. It is distinct from other models in that it categorizes students into four dimensions rather than just a few groups. This allows for more detailed analysis of individual student preferences and tendencies when it comes to their learning style. Following the main four dimensions of the FSLSM(Graf, 2007).

- Active/Reflective style of learning
- Sensing/Intuitive style of Learning
- Visual/Verbal style of learning
- Sequential/Global style of learning

The first dimension looks at how active or reflective the student tends to be when they are engaging with material; this helps teachers understand if they need to provide more guidance or allow them space to explore on their own. The second dimension examines whether the student has a preference towards sensing information through tangible experiences or prefers intuiting abstract concepts; this can help inform instructional strategies such as providing hands-on activities versus theoretical discussions. The third dimension looks at visual versus verbal approaches, while the fourth considers sequential versus global thinking processes - both important considerations regarding how best an individual should be taught certain topics and skillsets.

In summary, then, Felder & Silverman's Learning Style Model provides valuable insights into all aspects of an individual's approach towards education by looking beyond simple groupings based on broad characteristics like age or gender allowing us better tailor teaching methods accordingly so as get the maximum benefit out our instruction efforts.

C. Performance Metrics

K fold Cross Validation

Cross-validation is a technique used to estimate the performance of a machine learning model, ensuring that the model can generalize to new, unseen data(Battula, 2021).

MSE (Mean Squared Error), Bias, Variance

MSE (mean squared error) is a commonly used metric for evaluating the performance of regression models in machine learning. It quantifies the difference between the predicted values from the model and the ground truth or actual values in the data set. The difference between the

MSE and its expected value is composed of two components, bias and variance, which together form the bias-variance trade-off (Khan & Noor, 2019).

Bias refers to the tendency of a model to consistently under-predict or over-predict the actual values in the data set. A high bias indicates that the model is not fitting the data well and is underfitting. On the other hand, a low bias indicates that the model is fitting the data too well and may be overfitting(Fahse et al., 2021).

Variance refers to the variability of the model's predictions for different training sets or data samples. A high variance indicates that the model is too complex and overfits the training data, while a low variance indicates that the model is too simple and underfits the training data(Erickson & Kitamura, 2021)

III. RELATED WORKS

The research conducted by (Tamada et al., 2021) presents information about using Moodle logs and machine learning techniques for the identification of the earning style of the students in the online learning environment. The courses have been evaluated under three stages of completion of the course as 40%,60% and 80%. As the variables, they have chosen forum posts, access of quizzes as well as chat logs. For identification of the learning style, it has been used machine leaning classification algorithms as : Random forest (RF), Gradient Boosted Trees (GB), Logistic Regression (LR), Decision tree (Deep Learning (DL), and Support Vector Machine (SVM) and Naive Bayes (NB), Random forest algorithm has given a optimal accuracy of 81% in the evaluation.

(Rasheed & Wahid, 2021) the research presents information about the use of machine learning classification techniques for the identification of the learning style of the students, the learning style has been designed according to the FSLSM and have considered the Moodle logs have been used as the attributes. Support Vector Machine (SVM) was found to be most accurate when it came to predicting learner's dominant intelligence with an accuracy rate of 45.55%.

In this experiment,(Abdullah et al., 2015) 35 computer science department students were involved in using Moodle LMS for their data structure course designed according to the FSLSM model using Moodle logs. all student activities were logged through the system so any wanted features could be extracted at any time during or after completion of the course. At the end of each lesson, there was also a quiz which tested understanding on what had been taught throughout that particular session - providing invaluable feedback on how well they had learned from their experience with online teaching methods compared with more traditional ones used before its introduction into classrooms worldwide. For the identification of the learning style the research has used ROV curve-based techniques.

Another research by (Ikawati et al., 2020) has been conducted to identify the learning style of the students in the Moodle learning environment using Moodle logs as the attributes. The 65 students have been selected as the data sample for the research. As the machine learning algorithm they have used Decision Tree and ensemble Learning for the data classification. The results shoes that Decision tree gives an accuracy of 92% while the Gradient Boosted Tree give 88% of accuracy.

This study (Sianturi & Yuhana, 2022)presents a new literature-based method for estimating learners' automatic and dynamic learning styles. This method is based on the ILS questionnaire and student behavior on the LMS, which are then used to generate learning style results that can be used as labels in datasets. Three classifications were tested: decision tree, naive Bayes, and K-nearest neighbor; these models were evaluated using Python with sklearn via two types of tests – 80:20 train split test and K-fold 10 cross-validation test.

IV. METHODOLOGY

This section of the paper discusses the methodology of the research.

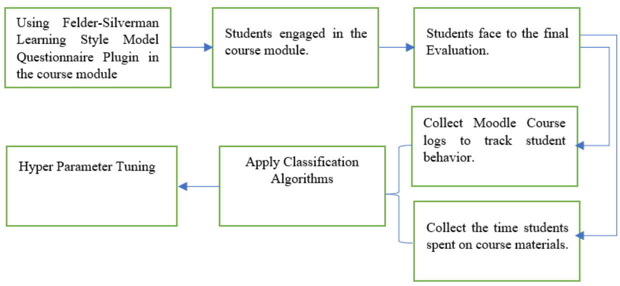

Figure 1: Methodology
Source: (Author)

As shown in the figure 01, Once students are enrolled with the course, they will be provided with FSLSM ILS questionnaire to be filled out within the system. To easier the usability of the ILS questionnaire in any of the Moodle environments, A new reusable plugin was developed to get the responses of the students. Then students are allowed to engage in the course activities as their preferences. At the end of the course their behavior int the learning environment was tracked using the Moodle logs already available facility in the Moodle environment and the time students spent in each activity in the Moodle environment using a new reusable plugin developed for the Moodle environment. Then as shown in below figure 02. Machine learning classification techniques were applied to train the data set for the purpose of determining the learning style. Then considering the efficiency of the Machin learning models, the optimal hyper parameters were identified through the Grid Search(George & Sumathi, 2020) and made changes accordingly.

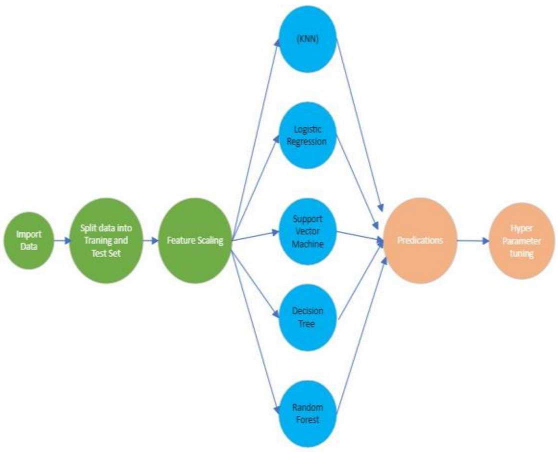

Figure 2: Machine Learning Process
Source: (Author)

A. Time Tracking Plugin for Moodle

This is one of the major contributions of the research in deciding the learning style of the students. In Moodle platform there are mechanisms for counting the time spent for completing an assignment like tasks, but there is no methodology for tracking how much time a user spends on all of the activities relevant to the course module. For this, it was developed a separate new plugin for counting time. A snapshot of the interface is shown below

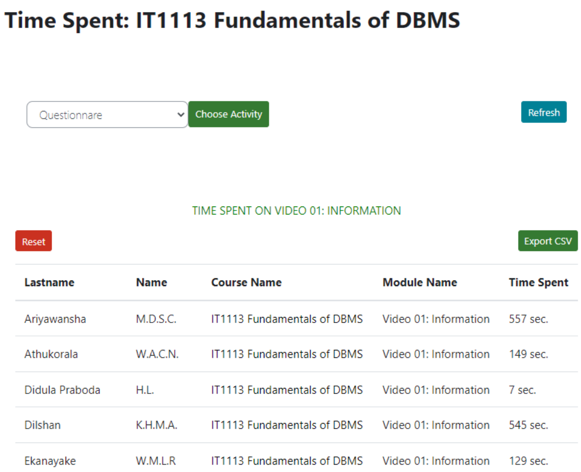

Figure 3: Machine Learning Process
Source: (Author)

The plugin operates on every course activity page and uses JavaScript libraries to record the time spent when a user accesses a course activity that has been plugged with the plugin. The recorded time is stored in the Moodle database and can be retrieved using PHP when a query is made. Each user is assigned a unique ID from the Moodle format, making it easy to track the time each individual student spends on an activity. The recorded time is in milliseconds but is then converted to seconds. Teachers and course administrators, who are privileged users, have access to the time-spent data and can also download it in CSV format. Students do not have access to the data collected. The plugin is connected to a Moodle table called prefix_timeque, where all the time-spent data is stored.

B. Data set

To collect the required data for model development to analyze the students' learning style, Two main course modules were designed as Fundamentals of Database Management Systems and Data Structures and Algorithms for the undergraduates of the General Sir John Kotelawala Defence University. Each data sample consisted of 150 undergraduates. Here it presents results only for the one-course module. In the course designed processed, it followed the guidelines of the FSLSM(Abdullah et al., 2015), (Quinn & Gray, 2019)model for designing each activity, preserving the rules for identifying learning style according to the FSLSM model. The following table shows the designing of the classification rules (f: Access frequency, T: Time spent)

Table 1: Classification Rules
Source: (Author)

Dimension	Learning Activity	Learning Style	Expected Behaviour	f	T
Processing	Forum posts	Active	Post/Reply	x	T
		Reflective	View (Minimum visits)	x	T
	Exercises	Active	Visit	x	T
		Reflective	No Visit (Minimum visits)	x	T
Input	Videos/Chars Images/Graphs (V_C_I_G)	Visual	View	x	T
		Verbal	No View	x	T
	Notes	Visual	View	x	T
		Verbal	No View	x	T
Perception	Contents	Sensing	Concrete Contents	x	T
		Intuitive	Abstract Contents	x	T
Understand	Course Outlines	Global	Course Outlines View	x	T
		Sequential	No View Visit (Minimum visits)	x	T

Once the data was acquired, machine learning classification algorithms such as Decision Tree Classifier, Support Vector Machine, Logistic Regression, K-Nearest Neighbors and Random Forest were applied to train the models. In this, each dimension of the FSLSM was separately trained to get the results.

V. RESULTS & DISCUSSION

In the FSLSM model, there are four main Dimensions as Input, Perception, Processing and Understanding dimensions. Each dimension was applied classification algorithms and the results are shown below.

A. Input Dimension.

Table 2: Summary of the Results :Input Dimension

Dimension / Algorithm	Input Dimension			
	Accuracy	Precision	Recall	F1
Decision Tree	95%	82%	80%	77%
Logistic Regression	61%	34%	42%	37%
Random Forest	85%	67%	73%	69%
Support Vector Machine	71%	56%	54%	55%
K-Nearest Neighbors	60%	36%	43%	38%

As shown in Table 02 decision tree algorithm has performed with 95% of accuracy among the other classification algorithms. Based on the provided results, the model has a relatively high accuracy of 95%, indicating that the model's predictions are mostly correct. The precision is also relatively high at 82%, which suggests that a significant portion of the predicted positive cases were correct. The recall is decent at 80%, indicating the model can identify the most actual positive cases. Finally, the F1 score is 77%, which measures the balance between precision and recall. Overall, the model seems to perform well on the given task, balancing both precision and recall reasonably well. And According to the cross-validation results of the model, it has 96% of accuracy and a minimum of Standard Deviation value of 10. The standard deviation of 10 suggests that some variations in the classifier's performance were observed between individual samples or repetitions of the experiment, but the level of variation is also considered acceptable. As minimum. With an MSE of 0.011, bias of 0.008, and variance of 0.004 calculated for the model, it seems that the model has a low bias and moderate variance, which is a positive sign, given that a lower bias corresponds to a better fit of the model to the data and moderate variance suggests that the model is not overfitting nor underfitting the data.

B. Perception Dimension

Table 3: Summary of the Results Perception dimension

Dimension / Algorithm	Perception			
	Accuracy	Precision	Recall	F1
Decision Tree	80%	75%	72%	70%
Logistic Regression	44%	49%	36%	35%
Random Forest	61%	50%	41%	44%
Support Vector Machine	57%	51%	44%	44%
K-Nearest Neighbors	66%	47%	51%	49%

Looking at the values provided in your question, the model has an accuracy of 80%, precision of 75%, recall of 72%, and F1 score of 70%. With an accuracy of 80%, the model is performing relatively well. However, the precision and recall scores are in a precise level. n. Here the cross-validated accuracy gave 78% and a standard deviation of 9.72. This is a moderate value when compared to the other trained model. But the Decision tree here has given the values of the maximum accuracy. In a comparison of the performance of Bias and Variance values the model has MSE value of 0.023 which is moderate, Bias value of 0.007 and Variance 0.005, as these values are not much higher model not show the qualities of underfitting or overfitting.

C. Processing Dimension

Table 4: Summary of the Results: Processing Dimension

Dimension / Algorithm	Processing			
	Accuracy	Precision	Recall	F1
Decision Tree	90%	94%	92%	92%
Logistic Regression	61%	67%	78%	63%
Random Forest	66%	57%	58%	57%
Support Vector Machine	71%	84%	83%	83%
K-Nearest Neighbors	42%	41%	45%	42%

Based on the results, a model with an accuracy of 90%, precision of 94%, recall of 92%, and F1 score of 92% appears to be performing well. The cross-validation accuracy is also in the rate of 81%, and SD is 8.16, that show low standard deviation value implies that the values in a dataset are clustered closely around the mean and the data points have a small variation or dispersion from the mean, and most of the values are relatively similar to each other. The MSE, Bias and Variance values are consequently 0.034, 0.018, 0.007 that low in consideration that not give an insight of the underfitting or overfitting of the model.

D. Understanding Dimension

Table 5: Summary: Understanding Dimension

Dimension / Algorithm	Understanding			
	Accuracy	Precision	Recall	F1
Decision Tree	95%	83%	80%	78%
Logistic Regression	74%	40%	41%	40%
Random Forest	85%	42%	50%	46%
Support Vector Machine	90%	70%	62%	64%
K-Nearest Neighbors	47%	23%	27%	24%

Based on the given search results, This model, with an accuracy of 95%, precision of 83%, recall of 80%, and F1 score of 78% appears to be performing moderately well. In the cross-validation, the accuracy has been given as 81% with a Standard deviation value of 6.14 which implies that the values in a dataset are clustered closely around the mean, and the data points have a small variation. And consequently, MSE, Bias and variance value has given 0.056, 0.042 and 0.008 which has moderate value and not implies of Underfitting or overfitting data.

E. Grid Search for Model Optimization

Grid search is a method used in machine learning to tune the hyperparameters of a model and find the best combination of hyperparameter values that result in the highest performance. It involves creating a grid of possible hyperparameter combinations and evaluating the model's performance for each combination to determine which one yields the best results. In the parameter optimization,it was considered sklearn.tree.DecisionTreeClassifier library. They are considered the parameter criterion with function {"gini", "entropy"} and parameter Splitter with functions {"best", "random"}. As an average for all dimensions Gini function for the criterion parameter and the "Best" function for Splitter gave the more optimal value with the time of 0.001 seconds. The reason for giving optimal time value by "Gini" function over "Entropy" is This is because the calculation of Gini impurity involves a simpler mathematical function that only requires a single squared term. In contrast, the calculation of entropy requires a logarithmic function, which can be more computationally expensive to compute.

VI. CONCLUSION

The research was conducted with the intention of proposing an improved model for identifying the learning style of the students using machine learning techniques using FSLSM approach. The previous researchers have used only the Moodle default log data provided by the Moodle infrastructure. But the proposed models comprised of the main two variables as considering the frequency of accessing the course activities by the candidates according to the records provided by the Moodle logs and Time spend by students in each of the activity. Then classification algorithms were applied to train the model and Decision Tree classifier performed with an average 90% of accuracy for the all dimensions'.K-fold cross-validation was used to evaluate the performance of the model and the results shows the models are is in a good performance level. Moreover, for each dimension, MSE, Bias and variance values were calculated to Check the validity of the model.

The contribution of this experiment to the the research field is it has been proposed more descriptive new methodology by considering the frequency of access the course activities and the time spend on each task. Moreover, a reusable plugin was developed to track the tie students spend on each of the course activities. Furthermore models were trained using data collected in the higher education university undergraduates and validated Machine learning models were tested for identifying the leaning styles.

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