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Determining Learning Style Preferences of Learners

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ABSTRACT

The use of Information and Communication Technology (ICT) in education has been rapidly growing in recent years which has converted conventional classrooms teaching environments into online learning (OL) environment. Online learning system is gaining popular and widely accepted in the world due to the current pandemic due to COVID 19. This has created an opportunity to take online classes through several online learning platforms. This research was also done during pandemic. The data were collected from one of the undergraduate courses where there were 108 learners. The objective of the study is to determine the learning style preferences based on the learner's interactions data. one of the popular and widely used learning style model called Felder Silverman Learning Style Model (FSLSM) was implemented in this study to determine the learning preferences. The learners were classified according to the two dimensions i.e., *input* and *processing* of FSLSM. Further, two popular tree-based classifier such as *decision tree* and *random forest* were implemented. Decision tree had a better performance in terms of accuracy than random forest. This type of research is very much beneficial to the instructors, learners and researchers and administrators working in the field of online learning.

1. Introduction

Online learning (OL) is very popular and widely used approach to address the COVID 19 pandemic. It is also being considered as a widely recognized option to address drawbacks of traditional learning environments [1]. Learning Management Systems (LMS) act as a platform for online teaching learning methods. It generates varieties of data on learner's performance which provides the opportunity to implement several data mining algorithms to extract meaningful information. Kathmandu University uses moodle as LMS for online education. [2] The authors discussed that as the online learning matures, focus will be shifted from developing infrastructures and delivering information online towards improving learning and its performances. They also stated that the challenge of improving learning and performance largely depends on correctly identifying characteristics of a particular learner. So LMS should be able to incorporate the learner's characteristics when delivering the contents to the users. They further argued that, for the design of an effective personalized learning system, it is important to look into the personalization parameters. These factors affect the personalization mechanism that is to be implemented. The basic personalization factors are *Learning Style, Working Memory Capacity and Prior Knowledge.*

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This research focuses on the learning style factor. Hence the objective of this research is to determine learners learning preferences based on the performances in the moodle system. The term "learning styles" refers to the concept that individuals differ in regard to what mode of instruction or study is most effective for them [3]. Learning style is characterized as the strength, quality and inclination in which individuals get and process data. The traditional way of detecting students' learning styles is based on asking students to fill out a questionnaire where the actual behaviors of the learners towards the system are not reflected. So, this research focuses on the learner's log data which reflect the learner's actual behavior towards the system. There are several learning styles models such as FSLSM, VARK, Kolb, Honey and Mumford, and Grasha Riechman. However, FSLSM is considered to be the most popular due to its ability to classify learners on the basis of their preferences over four dimensions [4][5]. It uses Index of Learning Styles (ILS) questionnaire. [6] ILS was developed by Felder and Soloman and used as an instrument to assess preferences in four dimensions. Hence FLSLM is based on Index of Learning Style (ILS). These questionnaires define the dimensions of learning style on a scale ranging between +11 to -11 [7].

The four dimensions of FSLSM are *input, understanding, processing, and perception.* Each dimension has two poles which is mentioned in table 1. Each pole can be mapped with learner's behavior. ILS consists of total 44 questions (11 questions for each dimension with two choices for each item). The learner's preferences are corresponding to values between +11 and -11, which determine the learner's preference between two adjacent poles. This research addresses the research question i.e. *How can we implement the FSLSM method to determine and classify the students based on their log data*? So, the objective of the research is to classify the learners into different categories based on their log data. Further two popular tree-based classifiers are also implemented in the datasets to develop the model. The model predicts the degree of preference on learning style of the users based on their system usage behavior. Decision tree and random forest were found to be widely used from the previous studies and both these algorithms were implemented in this research to profile the students based on learning style [8][9][10].

Learners activities in the online system generate large amount of data which provides an opportunity for the analysis of the data to get meaningful information. Several data mining (DM) algorithms can be applied in these data. Educational Data Mining (EDM) is the application of DM techniques to educational data [11]. It is concerned with developing methods that discover useful knowledge from data originating from educational environments.

The similar research work to this study was done in the moodle data where DT was implemented for the learning style identification [10]. Online learning behaviors from the web log files were considered for this research. Another work was also done in the moodle data which has implemented K-means and Naïve Bayes [12]. In this study, input data was the online system access activity log. i.e., the system web log. [13] The analysis was done in the mooc data which has implemented neural network. Learners traces from the web log data were considered for this study. Some other algorithms like Fuzzy C means (FCM) algorithm were implemented in the moodle data which consists of online learning behaviors as set of materials accessed by the learners from moodle database log [14]. In another study, Fuzzy C means algorithm and artificial neural network (ANN) were implemented in the moodle database web log [15]. [16] K-modes and Naïve bayes algorithms were implemented in the moodle data. Online learning behaviors based on web log files were considered for this research. Supervised machine learning algorithm were implemented in mooc data which consist of user generated reviews [17]. The comparison of the performance of four classifiers (Decision tree (DT), bayes net (BN), random

Table 1. FSLSM dimensions and their adjacent poles

Input Dimension		**Processing Dimension**	
Visual	***Verbal***	***Active***	***Reflective***
Prefers visual representations	Prefers text and spoken objects	Discussing and participation	Think first, explorer
Understanding Dimension		**Perception Dimension**	
Sequential	***Global***	***Sensing***	***Intuitive***
Prefers information in linear tendency to make small step	Explorer, prefers to see big picture before understanding	Prefers in detail, Memorize facts	Prefers in innovation, Dislike repetition

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forest (RF) and naïve bayes (NB)) was conducted to classify the students learning behavior with respect to FSLSM dimension [8]. The obtained accuracies were DT: 63.26%, BN: 63.84%, RF: 72.77%, NB: 59.62% for *processing* and DT: 81.25%; BN: 61.25%, RF: 78.75%, NB: 60% for *input* dimensions. In another study [9], investigation of the student's activity log of 507 students was done with the objective to study different classification techniques such as *Naïve Bayes, Logistic Regression (LR), Conjunctive Rule (CR) and J48 Decision Tree* for detection and identification of student's learning styles. Classification accuracy of 87.42% was obtained for DT, which was greater than LR: 83.42%, CR: 75.38% and NB: 83.13%). Similarly, the authors investigated the effectiveness of DT to detect student's learning style [10]. The focus was to construct rules influencing learning styles of the students. In their work, they have analyzed the activity of 100 students and have achieved an accuracy of 87%. The research was conducted to investigate different personalization techniques implemented in tutoring system [18]. The research was based on historical behavioral data, web usage data, questionnaires and quizzes data. [19] The research was done to investigate the perspective on how artificial intelligence (AI) enhance learning on online systems especially on MOOCs. The authors in this research focused on two aspects: *Personalizing learning activities and personalizing learning support. Personalizing learning activities* includes modeling of activities on how the course is to be presented to the users whereas *personalizing learning support* includes ways of enhancing the user's experience while using the system.[20] The research was conducted to develop an intelligent system which provided personalized learning experience based on specific learning goals and learning styles. The learner model was based on Felder-Silverman's test to detect the learning style of each learner. Another study pointed out that the increase in online and mobile technologies, personalized learning is becoming more important as online courses like MOOCs often have students from many countries with different prior knowledge, expectations and skills [21]. The system should be able to customize to their needs. In this research, the authors proposed a personalized system which provided personalized recommendation to the learners. Association rules along with content and collaborative filtering techniques were implemented in this research. [14] Authors proposed an approach to provide the learning contents with adaptive user interface (AUI) components based on the learning styles of the learners. Felder-Silverman Learning Style Model (FSLSM) was used as the learning styles for this purpose. The experiment was conducted on engineering students for particular online course. The result suggested that adaptation of user interface components and contents can be achieved based on learning styles.

These previous studies suggest that it is necessary to consider some important factors such as FSLSM categories of learners, real-time captured usage data or learning behavior of learners on learning objects in the OL system and integration of learning style in learning system to provide personalized environment. With the technological revolution of the internet and the information overload, personalized learning system has become a promising solution for educational institutions to improve students' learning process. Hence study on learning styles of learners is very useful and of great importance in such environment as they can help the system to effectively personalize students' learning process.

2. Methods

The following methods were applied in this research such as: *Generation of users click stream vector from the activity log, Mapping of activities with respect to the FSLSM dimensions, Grouping the users based on their LS preference and generation of generalized dataset and Development of a prediction model*. The steps involved in the data gathering and processing phases are: *Export of data from moodle database, Extraction of page components and the events which can be carried by the user, Extraction of unique activities available in the system and Feature mapping of the events according to FSLSM.*

The data was collected from the moodle system. This file consists of records of 108 students and their interaction within the system. The field names exported from the system are shown in table 2.

Table 2. Attributes in the log file

Name	Description
Time	Time Stamp of the Log Record
User full name	Users Full Name
Affected user	Affected Users Full Name
Event context	Context of the Event
Component	Component Producing the Log Record
Event name	Name of the Event
Description	Description of the Event
Origin	Origin of the Log Record (Client / Web Server)
IP address	IP Address of the Device through which the User Logged in

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comment_view	discussion_subscribe	discussion_view	post_update	subscription_create	report_view	wiki_diff_view
0	5	21	0	1	0	0
0	0	0	0	0	0	0
1	5	84	0	2	0	1
0	5	51	1	1	1	0
0	17	133	1	1	0	0
1	13	63	4	1	0	0

Figure 1. Aggregations of events carried by the users

Figure 1 shows the total number of counts of the learners of different features. After the data exported from the moodle system, the next step was to process the data to generate users click stream vector and the activities were mapped according to FSLSM dimensions and their respective poles. Each event carried out by the users within the system is logged in the system. The user's behavior is determined by how the user used the learning objects available in the system. The major components available for the users to access in the system are shown in table 3. The events related with these learning objects are shown in Table 4 (as logged in the system). The user's activity in the system can be divided into two types: events initiated at client side and the events initiated at server side. For the analysis, only the events initiated at server were filtered out.

Table 3. Learning objects components available in the moodle system

Learning Objects Component	
Assignment	Chat
Feedback	File
File submissions	Folder
Forum	H5P
Level up!	Lesson
Overview report	Page
Questionnaire	Quiz
Stash	Submission comments
Survey	System
URL	User report
Wiki	

Table 4. Logged events within the system

Event names	
A file has been uploaded.	mod_hvp: attempt submitted
A submission has been submitted.	Post created
An item was acquired.	Post updated
Comment created	Quiz attempt abandoned
Comment deleted	Quiz attempt started
Comment viewed	Quiz attempt submitted
Content page viewed	Quiz attempt viewed
Course module completion updated	Response submitted
Course module viewed	Responses submitted
Course searched	Some content has been posted.
Course user report viewed	Submission created.
Course viewed	Submission updated.
Discussion created	Subscription created
Discussion subscription created	Survey response submitted
Discussion subscription deleted	User report viewed
Discussion viewed	User view leaderboard
Grade overview report viewed	User viewed Badge
Grade user report viewed	Wiki diff viewed
Lesson ended	Wiki history viewed
Lesson restarted	Wiki page map viewed
Lesson resumed	Wiki page updated
Lesson started	Wiki page version viewed
Message sent	Wiki page viewed
Zip archive of folder downloaded	

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After identifying the user's events, user's traces were extracted from the data in order to represent each learner's as a set of features that constructs the feature-vector for the study. For the development of a user-feature vector, the learner's click stream events were aggregated based on the *event type*, which identifies the types of events performed within the system. This grouping of activity leads to a calculation of the total number of different types of events performed by a user within the system. This resulted in the generation of users click stream vector, which provides an indication of frequency when an event was initiated by the users. Since the research objective is to focus on identifying learning profiles of the students based on FSLSM, the events of the students were mapped with the FSLSM dimensions.

As shown in Table 1, FSLSM model contains four dimensions and each dimension has two adjacent poles. The activities which can be carried by a user within a learning system can be mapped with the FSLSM dimensions and the preference of the user to those activity describes the inclination of users to different learning styles as described by FSLSM [5]. These types of activities which can be carried out within a learning system differs from system to system. So, as per the availability of the data, the grouping of the students was done on two FSLSM dimensions i.e., *input* and *processing*.

Table 5. Features Mapped with FSLSM and the events within the log

Learning Style	Features	System event description
	Processing	
	# file_upload	A file has been uploaded.
	# Subimssion_made	A submission has been submitted.
	#comment_post	Comment created
	#comment_edit/delt	Comment deleted
Active	#discuss_created	Discussion created
	#msg	Message sent
	#post_created	Post created
	#forum_post	Some content has been posted.
	#Wiki_create	Wiki page updated
	#comment_view	Comments viewed
	#discussion_subscribe	Discussion subscription created
	#discussion_view	Discussion viewed
	#post_update	Post updated
Reflective	#subscription_create	Subscription created
	#report_view	User report viewed
	#wiki_diff_view	Wiki diff viewed
	#wiki_history_view	Wiki history viewed
	#wiki_pagemap_view	Wiki page map viewed
	Input	
	#comment_edit/delt	Comment deleted
	#course_report_view	Course user report viewed
	#course_viewed	Course viewed
	#gradereport	Grade overview report viewed
	#userreport	Grade user report viewed
	#interactive_video	mod_hvp: attempt submitted
	#wiki_pagemap_view	Wiki page map viewed
	#wiki_history	Wiki page version viewed
	#comment_view	Comments viewed
	#discussion_subscribe	Discussion subscription created
	#discussion_unsubscribe	Discussion subscription deleted
	#discussion_view	Discussion viewed
	#msg	Message sent
Verbal	#post_created	Post created
	#forum_post	Some content has been posted.
	#subscription_create	Subscription created
	#wiki_diff_view	Wiki diff viewed
	#wiki_history_view	Wiki history viewed
	#wiki_pg_view	Wiki page viewed

Table 5 shows the mapping of the events with the dimensions and respective poles of FSLSM. After the mapping of the events, clustering analysis was carried out in order to determine the Learning Style (LS) preference of the students. Since the objective was the grouping of the students according to their activity traces, clustering was found to be the suitable approach. Similar approach for grouping users/learners according to their activity traces to create user profiles has been implemented in various previous studies [22,23].

The study in this research implements the *K-means clustering method* to group the students according to their behavior. The major objective of implementing clustering is to create the group of different learning profiles of students shown within the system. For this purpose, based on the previous works [22], k means clustering is used. The input for each cluster was their respective features mentioned in Table 4. The output of the clusters shows how the users are interacting within the system and about their learning pole preferences. K means clustering technique aims to partition the "n" observations into k clusters in which each observation belonging to the cluster with the nearest mean. The value of k is also responsible to determine the compactness of the clusters. According to FSLSM model, users who have higher preference to active learning style prefer the activities that are mapped to the active learning style (as shown in Table 5). Similarly, the users who uses visual activities tends to show higher inclination towards visual learning styles. So, the clusters thus formed can be assigned the cluster weight according to the feature means of the cluster formed as "*Very Weak Preference", "Weak Preference*", "*Moderate Preference*" and "*Strong Preference*" for the respective poles, which gives the LS pole preference of the users. Clustering has been widely used by researchers to group the students according to their learning profiles. It has been used in some works [22][14]. Clustering, in this work has been used as a substitute to the traditional way of obtaining the learning style of the users i.e., the questionnaire approach. These works have shown that k means clustering can be used to group students according to their profile. Also, k means works better for cases where we do not know how instances in a dataset should be grouped together. In this study, as described by FSLSM, students can be grouped together based on their learning style preferences but it is unknown at first about those clusters. So, based on this, k means was used.

The optimal number of clusters need to be determined during the implementation of K means clustering. Silhouette method was applied to find optimal number of clusters where the average silhouette was calculated for varying number of k and it was found that the maximum value of the silhouette was found at k=4. The following figures (Figure 2-9) shows the plots to find the optimal number of clusters (K) using *elbow* point and *silhouette* methods. In elbow point method, the number of clusters is selected at the point where an elbow is formed whereas for the average silhouette method, the point which gives higher silhouette value is determined as the optimal number of clusters to be formed. From the figures, it was found that the elbow is formed at k=4. Also, for k=4, it resulted in the higher average silhouette value so the optimal number of clusters to be formed is selected as 4.

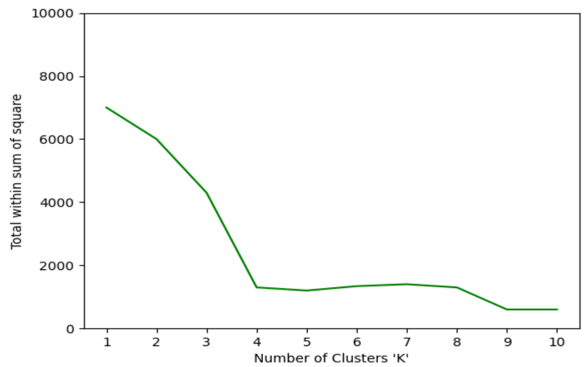

Figure 2. Elbow point graph to determine optimal "K" for active preferences

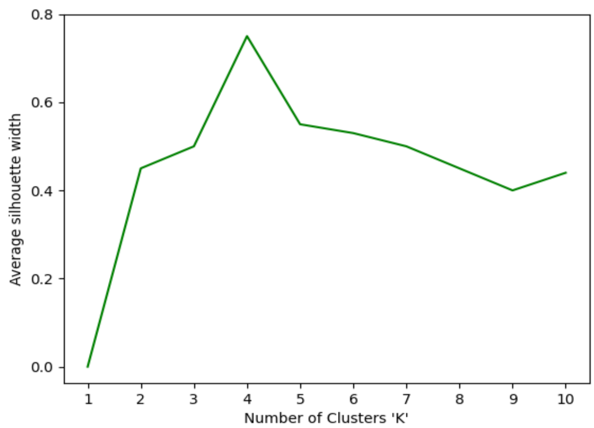

Figure 3. Silhouette graph to determine optimal "K" for active preference

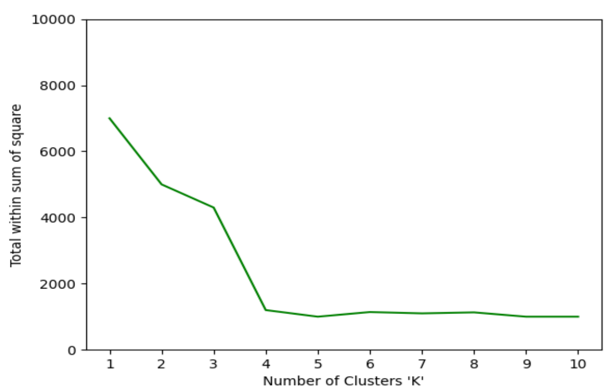

Figure 4. Elbow point graph to determine optimal "K" for reflective preferences

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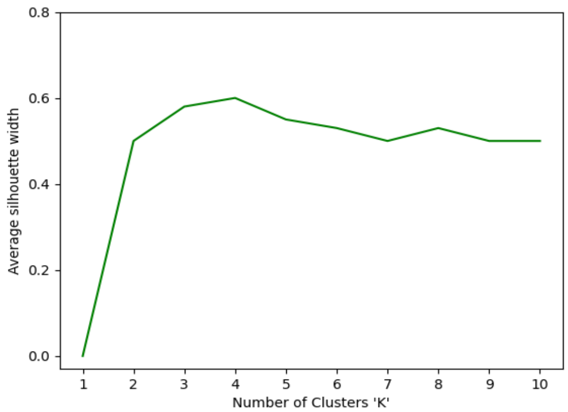

Figure 5. Silhouette graphs to determine optimal "K" for reflective preferences

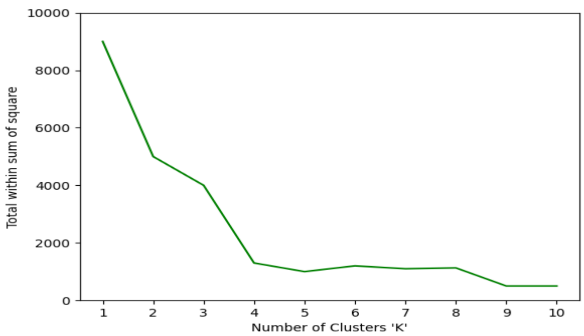

Figure 6. Elbow point graph to determine optimal "K" for visual preferences

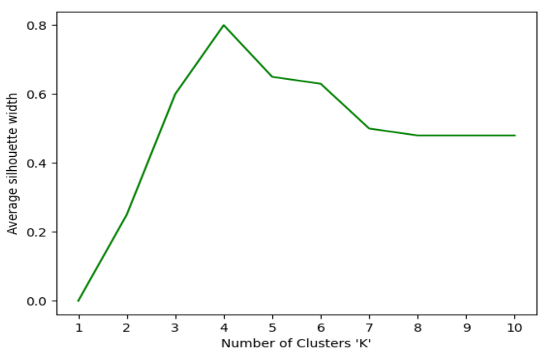

Figure 7. Silhouette graphs to determine optimal "K" for visual preferences

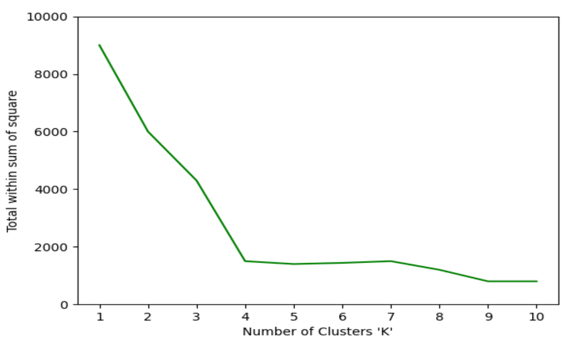

Figure 8. Elbow point graph to determine optimal "K" for verbal preferences

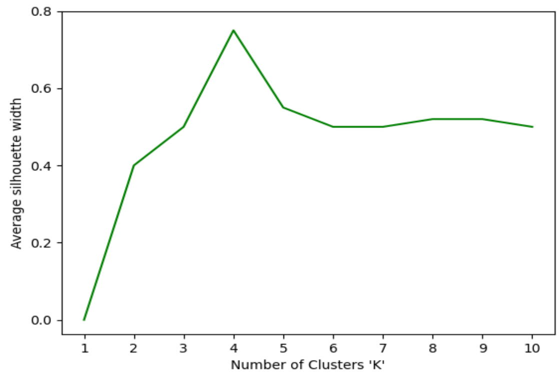

Figure 9. Silhouette graphs to determine optimal "K" for verbal preferences

3. Results

The objective of this research is to classify the learners under input and processing dimensions of FSLSM. Hence the learners were categorized into different classifications according to their log activities.

Table 6. Distribution of Learning Style pole preferences of students

	Very Weak	**Weak**	**Moderate**	**Strong**
	Processing Dimension			
Active	75	26	6	1
Reflective	66	24	11	7
	Input Dimension			
Verbal	66	26	9	7
Visual	1	81	23	3

Table 6 suggests that for *active learning style*, most of the users i.e., 75 out of 108 are showing *very weak* preference, which suggests that the learners have less access to the active pole activities within the system. Further, 24 students have weak preference for *reflective* and 7 students shows *strong preference* towards *reflective learning style*. Similarly, 23 students show moderate preference towards *visual learning style* but only 3 have *strong preference* for visual learning style. The result obtained from table 6 is very helpful to the instructors as the instructors of a particular course can get an overview of the learning style preferences of the learners which helps them to design learning objects accordingly. The behavior shown by the users on the learning objects is the reflection of their learning behavior. If the users show higher inclination towards the visual learning style then they tend to access the learning objects mapped with visual preferences. So, labeling of the users was done on the basis of cluster analysis and mean of the features associated with each group from lower group mean to higher group mean was termed as "*Very weak*", "*Weak*", "*Moderate*", and "*Strong*". FSLSM is helpful in grouping learners together based on their learning style preferences. So, clustering technique is applied for the initial grouping to label the data. The optimal number of clusters is found to be 4 (figures 2-9).

Dimension score gives the users preferred dimension based on Index of learning style (ILS) (learning preference for learners for each adjacent pole of FSLSM dimensions combined together). For the learner's group, the score obtained from two learning style of a dimension is summed up to get the dimension preference. For example, a learner with a *strong preference* for active learning with a score of + 3 and a *moderate preference* for reflective learning of - 2. The total of these two weightings is + 1 which suggests *moderate active* preference for *processing* dimension. Similarly, cluster value aggregation matrix can be generated to distribute the learning style preferences of the users. This matrix provides a generalized learning style preference of the user's behavior for the respective complementary poles of the dimensions. In accordance to this, respective adjacent poles of the dimensions can be aggregated to determine the dominant learning style. For example, a user with a strong preference for *verbal* learning is of score +3 and moderate for visual is of score -2. These two can be summed up to get a total score of +1 which indicates a moderate verbal preference. The cluster weight aggregation matrix for each dimension (combination of two adjacent poles) is shown in Table 7. Based on these calculations, each learner can be represented as a combination of feature vectors of their respective poles and the dimension score is calculated as:

Generalized feature vector = Pole 1{Feature vector}, Pole 2{Feature vector}, Dimension score

where, *Pole 1{feature vector}* and *Pole 2{feature vector}* represent features related to *Pole 1* and *Pole 2* respectively and dimension score represent predominant learning style related to the dimension. The "Dimension score" value shows the preferred learning style preference of the student.

Table 7 shows the distribution of the learning profiles of the students according to their learning styles for *input* and *processing* dimensions. It is based on ILS and FSLSM and shows how the values of the poles (adjacent poles of the related dimensions) can be grouped together based on the Index of learning style (ILS) and learning style preference to get the users preferred preference dimensions.

Table 7. Aggregation of cluster value weight of learning style [24]

			Active		
		Very weak (0)	**Weak (1)**	**Moderate (2)**	**Strong (3)**
	Very weak (0)	Balanced	Moderate Active	Strong Active	Strong Active
Reflective	**Weak(-1)**	Moderate Reflective	Balanced	Moderate Active	Strong Active
	Moderate(-2)	Strong Reflective	Moderate Reflective	Balanced	Moderate Active
	Strong(-3)	Strong Reflective	Strong Reflective	Moderate Reflective	Balanced
			Visual		
		Very weak (0)	**Weak (1)**	**Moderate (2)**	**Strong (3)**
	Very weak (0)	Balanced	Moderate Visual	Strong Visual	Strong Visual
Verbal	**Weak(-1)**	Moderate Verbal	Balanced	Moderate Visual	Strong Visual
	Moderate(-2)	Strong Verbal	Moderate Verbal	Balanced	Moderate Visual
	Strong(-3)	Strong Verbal	Strong Verbal	Moderate Verbal	Balanced

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Table 8. Distribution of data (Learning style degree of dominance of the students) in the datasets generated from the activity log

Data Distribution for Input Dimension	
LS preference	**Number of Students**
Balanced	24
Moderate Verbal	9
Moderate Visual	71
Strong Visual	4
Data Distribution for Processing Dimension	
LS preference	**Number of Students**
Balanced	84
Moderate Active	2
Moderate Reflective	16
Strong Reflective	6

Table 8 shows that for *input dimension,* most of the learners i.e., 71 out of 108 falls in *moderate visual* category. Similarly, for the *processing dimension*, most learners i.e., 84 out of 108 falls in *balanced* category. This information is very useful to the instructors to design the learning content accordingly. Also, these datasets generated can be used to train the machine learning model to develop a predictive model to classify the student's profile according to their learning styles. The *input* and *processing* dimensions are only considered in this study because the available events and learning objects were only possible to map with respect to these two dimensions. After the identification of learning style preferences and labeling of an individual students, predictive model was developed based on the generated datasets. A tree-based classifier such as *decision tree* and *random forest* were implemented to develop a learning style (LS) identification model to classify the students profile based on their interaction behavior.

Table 9 shows the result after implementing DT and RF. It includes accuracy, precision and recall of the algorithms implemented for two datasets generated for *input* and *processing* dimensions. The result shows that for *processing* dataset, DT gave an accuracy of 83.333% and RF 82.40%. Similarly, for *input* dataset, DT gave an accuracy of 87.963% and RF 78.703%. RF was found to have a better precision score for *processing* dimension dataset but DT had a greater for *input* dimension dataset. The recall value of DT was found to be higher in both the cases than RF. In terms of accuracy, DT had a better accuracy than RF in both the cases which indicate DT performed better to identify learning style of the users.

Table 9. Performance of Decision Tree while building model predictive model for processing and input data sets

Algorithm	LS Dimension Dataset	Correctly classified instances (%)	Incorrectly classified instances (%)	Precision	Recall
DT	Processing	83.333	16.66	0.78	0.833
	Input	87.963	12.037	0.884	0.880
RF	Processing	82.40	17.59	0.83	0.824
	Input	78.703	21.296	0.747	0.787

4. Discussion

Learning style plays a vital role during the development of personalized learning systems. With the increasing use of learning management systems and a lot of data being gathered from such systems, it has made it easier to apply machine learning algorithms to automatically identify the learner's learning style over the learning process. The learner's traces within the system can be of great use for this process. The data collected in this way can help to understand how the users are interacting with the system and the learning objects, which in return will be a major considering factor in designing personalized and effective learning environments that are best tailored to the needs and characteristics of each learner, unlike the previous systems which consider delivering the same resource to all the learners. The effectiveness of personalized learning systems is dependent on how accurately the system can understand the learning preferences of the users. Moreover, identifying the various learning style preferences of users and increasing identification accuracy of learning styles contribute to the development of adaptive personalized systems. The cluster analysis used to group the students with respect to their LS preference helps the instructor to understand the various groups of learners present in a particular course and their behaviors towards the various learning objects within the system. This provides a clear view of the types of learning objects of the course contents to be provided to the learners. In addition, the classification model evaluation showed that the accuracy of DT is higher than RF. So, DT can be the better algorithm to be implemented to detect the learning style of the learners.

5. Conclusion

Through the analysis of the user's activity log data, it can be seen that the user's activity can be mapped with different learning styles preferences in accordance to the FSLSM model. Based on the user's preference to these activities the users can be grouped together. Learning systems have diverse activities and learning contents available within them and these activities differs from system to system. The initial step while detecting the users learning styles on the system is to identify these activates and to map these with respect to FSLSM model. Also, all those activities may or may not be mapped in accordance to the studied model. The log currently does not provide the navigation behavior of the students. Also, from the log, information of how the students perceive the information cannot be determined. Therefore, the inclusion of navigational and perception activity can further be incorporated while developing the learning objects. This includes inclusion of paging while accessing learning contents, back and next buttons, in application exercises, demo exercises, notes summary pages etc. The major stakeholders of this study can be researchers, learners, instructors and educational decision makers. Instructors and educational decision makers can get overview of the student's online learning behavior and based on it they can implement various instructional strategies. Researchers can understand about the learning styles and classification of learners.

The future work can be: *Evaluation of the prediction power of different online attributes in predicting learning styles.* This includes the study of sensitivity of the learning objects features to the performance of the classifiers, the addition of other parameters like users grades on previous courses, time spent on accessing a particular object or page, students social and geographical characteristics to further develop the student model. Based on this study, personalized and adaptive system can be developed. An adaptive/personalized system should be able to differentiate the learners based on their activity and either provide or guide them with dynamic learning instructions. The instructions can be provided based on the adaptation factor either to increase the students' performance or motivation towards learning. So, the basic task that it can perform can be listed as: identify the users (it includes the determination of adaptation factors like Learning style, Prior Knowledge and Working Memory), identify the learning objects (it includes the task of filtering the learning objects to provide to the learners based on the adaptation factor) and guide the students (the system should guide the students during the learning process).

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