Personalization of Learning Management System using VARK

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Abstract: In the current scenario Learning Management System (LMS) an integrated web based learning environment and tool for instructional purpose is highly preferred educational to make learning available at any time anywhere to the learner. As most of the Learning Management System focuses more on providing a personalized learning environment based on user interests that will ease the process of learning. Each individual will have their own Learning style in which he/she understands, adapts and identifies new and concrete information. At this juncture identifying the learning style of the individual helps to provide a more personalized Learning Management System. In this paper we intend to study the usefulness of classification algorithms in classifying the raw data that serves as source for further learning style prediction. Thus the identification of the learning style using efficient data mining techniques improves the overall performance of the Learning management system.

Index Terms: Learning Management System, Classification Techniques, Learning Styles, Learning Environment.

1.Introduction

In the current digital era, most of the educational organizations show their interests in providing e-learning based solutions to their learner's to provide a sophisticated learning environment through Learning Management system (LMS) Learning Management system is used for e-learning practices that provides instructor to create and deliver content, monitor student participation and to evaluate student performance through a web domain based technology. In this juncture there arises need to Learning Management system to understand the Learning preferences of the Learner understanding the content to provide more personalized Learning Management system. In this scenario the prediction of learning style supports us to provide more personalized Learning Environment. The learning style is viewed as individual perception on acquiring information and converting as knowledge by various experiences from day –to-day life [1]. Each individual have their own style of learning based on their characteristics.

Learner style traces for decades in Kolb's model (1984) of experiential learning the learning styles can be viewed as four Accommodator, Converger, Diverger, and Assimilator. Each learning style have individual approach in understanding learners learning style, among these VARK model developed by Fleming is widely accepted to enhance its functionality with the recent technologies. The prediction of learning style that uses efficient data mining technique serves as effective tool in the process of personalizing LMS. The personalization of Learning Management system improves the overall performance of learning system by providing sophisticated Learning environment to the learners.

2.Literature Review

The Learning Management system (LMS) is a web domain based technology used for e-learning practices. It provides an instructor with a way to create and deliver content, monitor student participation and to evaluate student performance [25]. LMS consists of various interactive features in learning through discussions, video conferencing and discussion forums. Learning Management System is an integrated solution of learning that termed in various ways as (i) Course Management System (CMS), (ii) Learning Content Management System (LCMS), (iii) Managed Learning Environment(MLE),Learning Support Systems and Learning Platform. The LMS system is user centric learning environment that adapts and personalize learning environment based on learners preferences in learning[15].The Learning Management frameworks gathers information about learners from web log based on the learning activities by the learner and utilizes the information to identify various learning strategies that will the Learning system administration framework to personalize the Learning Management System to the Learner.

2.1 Learning styles

Learning style defines characteristics of each individual. Learning style will be more influenced by various factors of individual thought and feeling that a person's perceives, responds and interacts in his social environment. Instructors teaching tasks can be simplified by understanding the preferences of learning chosen by individuals. Learning styles consists of learning style questionnaires termed as Learning Style Inventories that is used to identify the learning style of individual [8]. Learner style traces for decades in Kolb's model (1984) of experiential learning the learning styles can be viewed as four (Accommodator, Converger, Diverger, and Assimilator).In Peter Honey and Alan Mumford adapted Kolb's experiential learning model, they aligned these stages to four learning styles named (Activist, Reflector, Theorist ,Pragmatist).Each learner will have their own way of learning things (Sarasin, 1999)[10].In the words of Bostrom, Olfman and Sein (1990) each educator employs various training methods to various group of people. Show (2012) witnessed that learning can be viewed as various group of strategies that influence the student's learning style. The learning style methodologies offer a bunch of learning style in that most of the researchers showed their interest in interpreting learning styles such as Kolb's Learning Style Inventory (LSI), Felder– Silverman Learning Model and VARK Learning style and Myers-Briggs Type Indicator. Each learning style have individual approach in understanding learners learning style, among these VARK model developed by Fleming is widely accepted to enhance its functionality with the recent technologies[9].

2.2 VARK MODEL

Neil Fleming VARK model and inventory suggest four modulator methods for identifying learning style of individuals as Visual Learning, Auditory Learning, Physical Learning, and Social Learning.

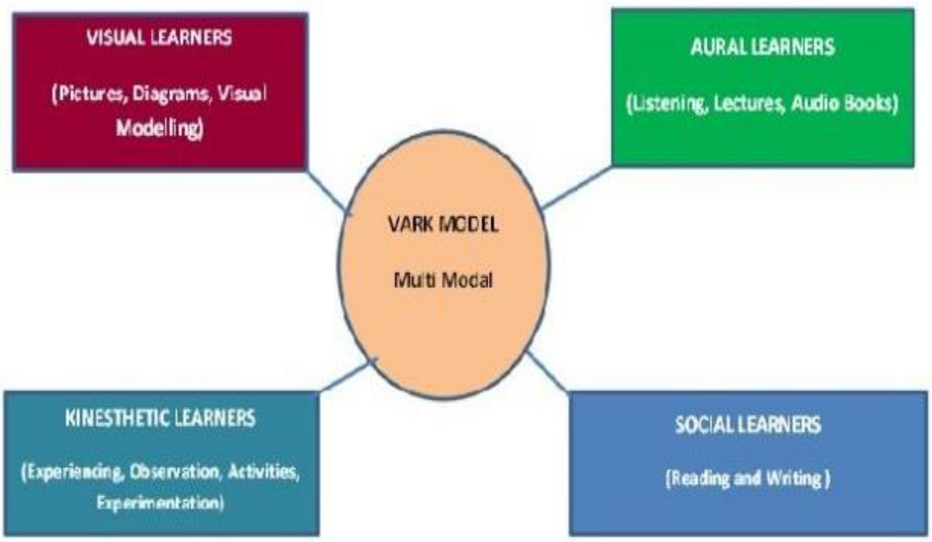

Figure 2: VARK Learning Style Model

•Visual Learners prefers to learn things from real time visual tools such as graphs, charts, diagrams, symbols.

•Auditory Learners learns from understands through listening such as lectures, discussions, tapes.

•Tactile/knithestic Learners prefer to learn using real time experiencing such as project work.

•Social Learners prefers to learn using social Skills like Reading and Writing

3.Methods and Materials

The new emerging discipline that inherits its traits from different literature sources including data mining, machine learning, psychometrics, and other areas of computational modeling, statistics, and information visualization that can be applied in handling educational sector and its data is known as Educational Data Mining[12]. The EDM is promising and ensures a better way in utilizing Educational Data Mining (EDM) with sequence of steps starts from evaluating information for interesting knowledge, identifying the required knowledge through continuous refinement and presenting the discovered patterns. The role of educational data mining in LMS differs for Instructor and learner in visualizing the data for the students it hould enhance the Learning Management System by giving personalized learning environment based on his preferences, on the other hand the discovered knowledge that can be utilized by the instructor for planning the activities to learners to give better learning experience [13]. The application of Educational Data Mining provides a wide range of solution to the Learning Management System. In the words of Castro [9], the application interests widely spread on analyzing learner's performance, understanding learner's interests to enhance curriculum for the courses, Methods for evaluating the learner, Feedback mechanism and identifying learner's behavior. Educational Data Mining (EDM) plays an important role in the process of learning as learning has been more personalized in the digital Era [15].

3.1 CLASSIFICATION ALGORITHMS

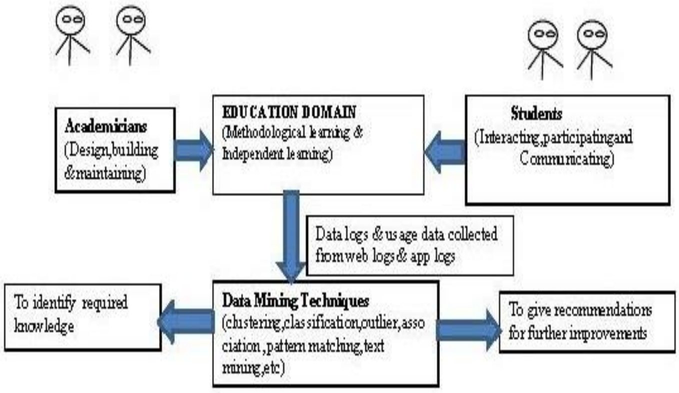

Figure 3.Typical Architecture of Educational Data Mining

Classification is a classic data mining technique based on machine learning. Classification is used to classify each item in a set of data into one of a predefined set of classes or groups. Classification from large chunks of data provided to the Learning Management System needs to be our first priority in utilizing data mining for personalizing LMS. There are various algorithms commonly used for classification of them are Decision trees, k-Nearest Neighbor, Naïve Bayes, Support Vector machines and so on.

Naive-Bayes: The Naive Bayesian works on stastical classification in predicting class members by probabilities belongs to a particular class. The Computational efficiency and simplicity makes the real world applications to widely use Naive Bayes and Bayesian networks for classifying data. It classifies data based on presence or absence of attribute value in the class .The naive Bayes works with small amount of training to identify required knowledge .This classification helps in identifying dissimilarities in Learner 's data in LMS.

K-Nearest Neighborhood (KNN): This algorithm classifies data on classifying objects based on identifying nearest neighborhood in data training. The classification is based on object based learning or lazy learning in classifying data on approximate function estimation[13] .The majority vote of its neighbor is termed as K – nearest neighbors. The algorithm works on pattern matching and identifies the target function .This algorithm K-NN is severely affected by noisy data and non-accurate data will degrade the performance of K-NN in data classification.

Support Vector Machine (SVM): SVM is used for knowledge discovery through classification, regression and outlier's detection [10]. SVM is considered advantageous and efficient in its high dimensional spaces, efficient memory management but if the sample sizes become greater the performance becomes poor SVM will not support for probability estimates.

Decision Tree: The Decision tree classifiers are widely used classification technique it uses tree like structure for decision making which starts with parent node and traverse to child nodes. It works based on the relationship among attributes and its importance .The decision tress is useful in the analysis of numerical and categorical data. The decision tree algorithm uses greedy approach and works in a top-down recursive divide and-conquer manner. The ID3 works on Information gain as attribute selection criteria and analyses the data for classification. The J48 algorithm is a successor of ID3 algorithm organized in hierarchy it filters data and train data in model training and uses root and internal nodes as test cases [14].

Rule Learners Classification Algorithm: The classification of data using oneR rule learner algorithm is simple and widely used for one level decision tree based on a set of rule expressed in decision tree to test on one particular attribute. This algorithm produces promising rules in characterizing the data [25]. The JRIP is also an effective decision tree algorithm that classifies data based on incremental error –pruning from initial rule set to a growing set using heuristic method finding the greatest reduction of error on pruning set of data.

4. Proposed work

In the proposed work (i)we intend to study the usefulness of classification algorithms in classifying the data that serves as source for further learning style prediction (ii)To analyze the Learning characteristics of learner to identify their Learning Style from the Prevailing data . Thus the identification of the learning style using efficient data mining techniques improves the overall performance of the Learning management system The prediction of learning style in personalizing Learning Management System (LMS)[15].The performance is identified by using various classification algorithms.

The proposed investigation starts by using Decision trees to classify the dataset of the learners based on the Learning style inventory questionnaires preferred by the Learners. Decision trees are used for classifying data as nodes and branches by traversing through decision paths in classifying data [7]. The motive of this paper to use decision tree as classification algorithm to predict the learning style based on the preferences by the Learners.
Data Mining Process for Knowledge Discovery.

The data mining process for predicting Learning Style to personalize Learning Management System contains sequence of steps

Data Collection

The raw data consists of information of the learner and his/her choice in answering the Learning Style inventory questionnaires .

Data Pre-processing

The preferred choices should be matched with VARK questionnaires and the choices should be transformed into appropriate format that includes process of data cleaning and data processing ,data reduction and data transformation.

Data classification for learning style prediction

Initially we started investigating using decision tree algorithm J48 for classification as it is highly preferred by various researcher s for analysis .we also intended to utilize Rule classification algorithm Decision Table and Navies Bayesian Net based Navies Bayes for further classification by using data mining Tool WEKA for investigation in classifying raw data that helps to predict the learning style.

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Relation: sasiproCSV

No.	1: id Nominal	2: age Numeric	3: GENDER Nominal	4: OCCUPATION Numeric	5: Education Level Numeric	6: Visual Nominal	7: Auditory Nominal	8: READING Nominal	9: KINESTHIC Nominal	10: **Result** Nominal
1	ID12...	48.0	FEMALE	1.0	1.0	yes	NO	NO	NO	AUDITO...
2	ID12...	40.0	MALE	3.0	3.0	YES	NO	YES	YES	AUDITO...
3	ID12...	51.0	FEMALE	0.0	0.0	YES	YES	YES	NO	KINEST...
4	ID12...	23.0	FEMALE	3.0	3.0	NO	NO	YES	NO	KINEST...
5	ID12...	57.0	FEMALE	0.0	0.0	NO	YES	NO	NO	VISUAL
6	ID12...	57.0	FEMALE	2.0	2.0	NO	YES	YES	NO	VISUAL
7	ID12...	22.0	MALE	0.0	0.0	NO	NO	YES	NO	KINEST...
8	ID12...	58.0	MALE	0.0	0.0	YES	YES	YES	NO	AUDITO...
9	ID12...	37.0	FEMALE	2.0	2.0	YES	NO	NO	NO	VISUAL
10	ID12...	54.0	MALE	2.0	2.0	YES	YES	YES	NO	VISUAL
11	ID12...	66.0	FEMALE	0.0	0.0	NO	YES	YES	NO	AUDITO...
12	ID12...	52.0	FEMALE	0.0	0.0	YES	YES	YES	YES	VISUAL
13	ID12...	44.0	FEMALE	1.0	1.0	NO	YES	YES	YES	READI...
14	ID12...	66.0	FEMALE	1.0	1.0	YES	YES	YES	YES	AUDITO...
15	ID12...	36.0	MALE	0.0	0.0	NO	YES	YES	YES	KINEST...
16	ID12...	38.0	FEMALE	0.0	0.0	YES	YES	YES	YES	KINEST...
17	ID12...	37.0	FEMALE	2.0	2.0	NO	NO	NO	YES	READI...
18	ID12...	46.0	FEMALE	0.0	0.0	NO	YES	NO	YES	READI...
19	ID12...	62.0	FEMALE	0.0	0.0	NO	YES	NO	NO	AUDITO...
20	ID12...	31.0	MALE	0.0	0.0	YES	YES	YES	NO	AUDITO...
21	ID12...	61.0	MALE	2.0	2.0	NO	YES	NO	NO	READI...
22	ID12...	50.0	MALE	2.0	2.0	NO	YES	YES	NO	VISUAL
23	ID12...	54.0	MALE	0.0	0.0	NO	YES	YES	NO	READI...
24	ID12...	27.0	FEMALE	0.0	0.0	YES	YES	YES	YES	READI...
25	ID12...	22.0	MALE	2.0	2.0	YES	YES	YES	NO	READI...
26	ID12...	56.0	MALE	0.0	0.0	YES	YES	YES	YES	VISUAL
27	ID12...	45.0	MALE	0.0	0.0	NO	YES	YES	YES	VISUAL
28	ID12...	39.0	FEMALE	1.0	1.0	NO	NO	YES	NO	READI...
29	ID12...	39.0	FEMALE	3.0	3.0	YES	NO	YES	YES	AUDITO...
30	ID12...	61.0	MALE	1.0	1.0	NO	NO	YES	NO	AUDITO...
31	ID12...	61.0	FEMALE	2.0	2.0	NO	YES	YES	NO	AUDITO...
32	ID12...	20.0	FEMALE	2.0	2.0	NO	YES	NO	NO	KINEST...
33	ID12...	45.0	MALE	1.0	1.0	YES	YES	YES	NO	KINEST...
34	ID12...	33.0	FEMALE	3.0	3.0	YES	YES	NO	NO	AUDITO...
35	ID12...	43.0	MALE	0.0	0.0	NO	YES	YES	NO	KINEST...
36	ID12...	27.0	FEMALE	2.0	2.0	NO	YES	YES	NO	KINEST...
37	ID12...	19.0	MALE	3.0	3.0	YES	YES	YES	NO	KINEST...
38	ID12...	36.0	FEMALE	0.0	0.0	YES	NO	YES	NO	AUDITO...
39	ID12...	43.0	FEMALE	0.0	0.0	YES	YES	YES	NO	AUDITO...
40	ID12...	66.0	FEMALE	2.0	2.0	NO	NO	YES	NO	VISUAL
41	ID12...	55.0	MALE	0.0	0.0	NO	NO	YES	YES	VISUAL
42	ID12...	47.0	FEMALE	0.0	0.0	YES	NO	YES	NO	AUDITO...
43	ID12...	67.0	MALE	2.0	2.0	YES	YES	NO	NO	VISUAL
44	ID12...	32.0	FEMALE	0.0	0.0	YES	NO	YES	YES	KINEST...
45	ID12...	20.0	MALE	2.0	2.0	YES	YES	YES	YES	VISUAL
46	ID12...	64.0	MALE	2.0	2.0	NO	YES	YES	YES	VISUAL
47	ID12...	50.0	FEMALE	1.0	1.0	YES	YES	YES	NO	AUDITO...
48	ID12...	29.0	MALE	2.0	2.0	NO	YES	YES	YES	AUDITO...
49	ID12...	52.0	MALE	2.0	2.0	YES	NO	YES	NO	AUDITO...

Figure 4: Attributes view in WEKA for classification

4.1 Performance Evaluation

The performance of the classifiers algorithms is evaluated using the following metrics
Precision: proportion of correct positive observation

Precision = True Positives / (True Positives + False Positives)

Accuracy: Proportion of total number of correct prediction

True Positives + True Negatives / True Positives + True Negatives+ False Positives+ False Negatives

Recall: Proportion of positives correctly predicted as positive

Recall = True Positives / (True Positives + False Negatives)

F-Measure: This is derived from precision and recall values. The F-Measure produces a high result when Precision and Recall are both balanced, thus this is very significant.

F-Measure = (2 * Precision * Recall) / (Precision + Recall)

RESULTS

The motive of this work is to identify attributes that contributes to the prediction of learning style initially out 17 attributes 10 attributes considered as predicting factors. We also intend to study about the performances of the classification algorithms (J48, REP TREE, Random Tree, Decision Stump and Navies, Bayes Net) to understand the usefulness of the classification outputs in Learning Style prediction.

Classification is a classic data mining technique based on machine learning. Classification is used to classify each item in a set of data into one of a predefined set of classes or groups. To evaluate the perform classification algorithms, the data set is loaded into WEKA as input and for each selected algorithm is experimented and output is obtained. After applying the various data mining algorithms the results are summarized as follows

J48 MODEL: The J48 algorithm a successor of ID3 algorithm that filters data and trains using internal nodes gave 94.166 where 565 instances were correctly classified 5.83333% 35 instances are classified as incorrect. The decision tree for the testing phase is presented.

REP TREE: J Rip, a propositional rule learner, that works based on association rules with reduced error pruning, shows 90.527% where 543 instances were correctly classified 9.33333% 57 instances are classified as incorrect.

Random Tree: Random Forest Trees (RFT) is machine learning algorithm based on decision trees that classifies with a method which makes predictions by averaging over the predictions of several independent base models. The output Shows 88.666% where 532 instances were correctly classified 11.33333% 68 instances.

Navies Bayes: Naïve Bayes is a probabilistic machine learning algorithm based on the Bayes Theorem .The classification output falls with 90.166% where 541 instances were correctly classified 9.8333% 59 instances are classified as incorrect.

Decision Stump: A decision stump makes a prediction based on the value of just a single input feature the classification output falls with 92.8333% where 557 instances were correctly classified 7.1666% 43 instances are classified as incorrect.

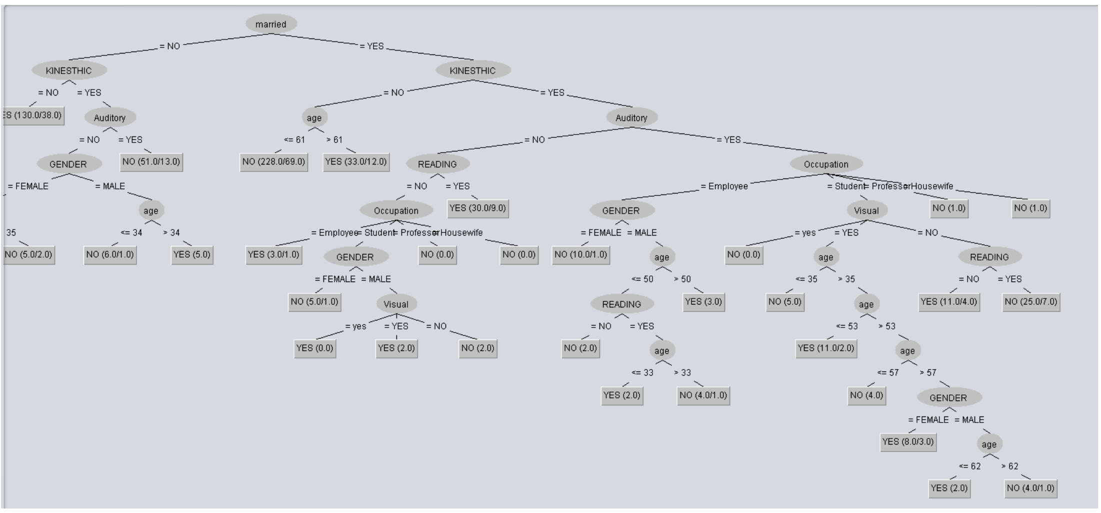

*Figure 5**J48 Classification Algorithm Tree in WEKA***

Table 1: Result Outputs of Classifier Algorithms

Experiment	Algorithm	Precision%		Recall%		F-measure%		Accuracy%	
		10 fold CV	20% Test Set	10 fold CV	20% Test Set	10 fold CV	20% Test Set	10 fold CV	20% Test Set
1	J48	94.3	88.1	93.3	89.6	93.7	87.9	93.333	89.583
2	REPTree	87.7	66.0	90.0	81.3	88.5	72.8	90.000	81.250
3	Random Tree	83.4	88.8	86.7	91.7	84.9	89.6	86.667	91.667
4	Naive Bayes	87.7	79.8	90.0	85.4	88.5	82.5	90.000	85.417
5	Decision Stump	88.5	88.9	91.7	91.7	89.8	89.6	91.667	91.667

4.2 Personalizing Learning Management System Using Learning styles:

In the process of Personalizing Learning management System for our preliminary investigation we sub- categorize learners into (i) Academic Learning (ii) post-Academic Learning (iii)General Learning and their preferences based on learning style prediction to identify their interest in personalizing LMS.

Table 2: Evaluation of Learning Style based on Learners Preferences

Characteristics	**Academic Learning**	**Post-Academic Learning**	**General Learning**
Visual	Highly preferred	Moderately preferred	Moderately preferred
Auditory	Moderately preferred	Moderately preferred	Less preferred
Reading	Less preferred	Less preferred	Highly preferred
Kinesthetic	Highly preferred	Highly preferred	Less preferred

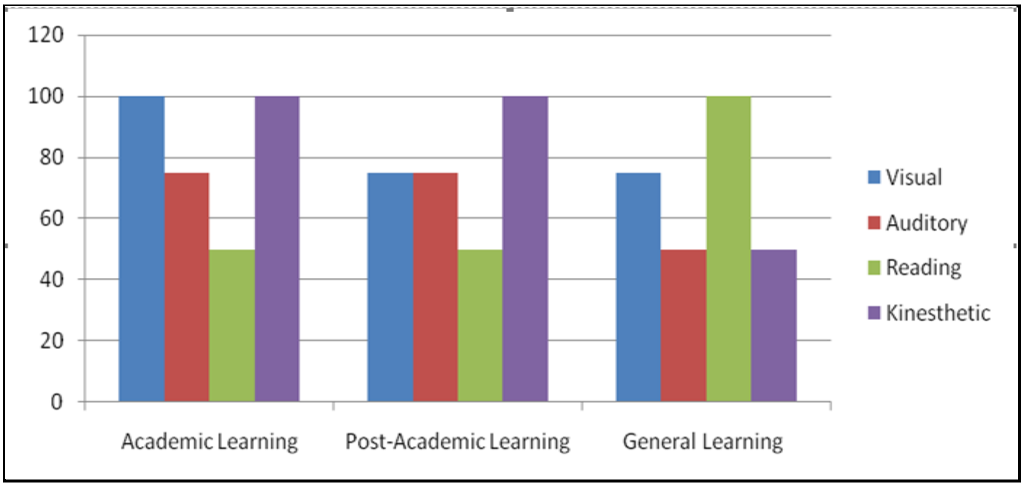

Figure 5: Classification of Learners Using VARK

Table 2 shows the preferences of the learners to personalize Learning Management System. The comparison is based on identified factors from the processed data classified using decision trees in WEKA data visualization tool .This helps us to identify the preferences of the learners and Fig 5 classification of Learner Using VARK has given us insight of adapting VARK Learning Style model with decision tree support in prediction of learning style using Data Mining to personalize Learning Management System.

5. Results and Discussion

In this paper, effort has been made to understand the usefulness of classification predict Learning preferences based on attributes associated with Learning Style. The use of WEKA which is a free desktop tool for data mining has shown that data mining today can be carried out without the challenge of big investment in analytical tools. The classification techniques were used to predict the Learning style of the Learners based on the data utilized.
The analyses above show that J48 (Decision Tree) with accuracy of 93.333% using 10 attributes and 10 fold cross validation is more appropriate in building the predicting model for the Learning style of the Learners based on the dataset. Compared to four other algorithm used in the study, J48 shows better prediction accuracy and followed by Decision Stump which have prediction accuracy of 91.667% for both 10 fold cross validation and 20% supplied test set. A closer look shows that though J48 has the highest prediction accuracy, Decision Stump has higher prediction accuracy over J48 when 20% supplied test set is used. It therefore meansthat

Decision Stump provides better generalization output compared to other classification tools. A likelihood reason for the performance of J48 on the test set may be the higher sensitivity of J48 to missingvalues.

Generally, different studies have found mixed outputs in terms of classification algorithm performances. For example REPTree performs better that J48 and M5P DecisionTree[6] While J48 has better accuracy compared to Naïve Bayes and Random Tree.

6.Conclusion and Recommendations

This paper achieved its motive by identify the influencing attributes of Learners preferences in learning style prediction and exploring the level of predicting accuracy of different algorithms in the WEKA environment. Future research can look into more attributes based on particular Learning Style Inventory that serves as prerequisite knowledge prior to taking some course and the use of large dataset for analysis. The work also gives us insight on learning preferences of Learners in understanding their Learning Style.

Thus the work promising results to extend in developing more efficient framework using data mining .The Learning Style prediction will improve the overall performance in personalizing learning environment .The investigation can be further extended by adapting various data mining techniques and algorithms in personalizing LMS to improve the overall performance of the Learning Environment.

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