J48-Based Decision Tree Algorithm in Detecting Kolb's Learning Style Preferences of Information Technology Students

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Abstract

Teacher education institutions developed interventions to augment both the Teacher's teaching and the Learner's learning process. Previous studies focused on detecting learning styles in e-learning using learning management systems and adaptive learning in the online learning process, specifically using the Felder-Silverman learning style model. On the contrary, this study aimed to develop a decision tree-based model to detect the Learner's learning style inspired by Kolb's learning style in a face-to-face learning environment. Knowledge discovery in databases through data mining was utilized using the J48 algorithm to develop a decision tree-based model. This study was participated by 408 out of 462 information technology students in a state university in the Philippines. The study's result was able to develop four J48-based decision trees with conditional rule models for activist, reflector, theorist and pragmatist learners. The evaluation of the decision tree models using confusion matrix and receiver operating curve showed a very high accuracy detection of every learning style (weighted average of 88-96%). This result recommends applying this in an actual system or computer application for easy and fast learning style detection based on the characteristics of the learners.

Keywords: confusion matrix, data mining, decision tree, learning style, machine learning

1. Introduction

Learning and the learning process are two complex progressions of individuals which involves various factors such as time, environment, belief, sex, social status, philosophies, religion and upbringing, among others. The learning gap is widely evident in heterogeneous classes in developing countries wherein determining the students' learning styles is neglected. The teachers' challenge is identifying the type of learners in their classroom considering that teachers may require variation in the teaching-learning process to cater to diverse learners' needs (Malik *et al*., 2019). Student learning style preferences have been presented and utilized in many schools in different countries in the learners' diverse settings and characteristics. A study in Mexico revealed that unfolding student learning style preference provides valuable information relative to education programs, better connection between the learner and the teacher and student empowerment through action (Franquesa-Soler *et al.*, 2019). Also, it may provide unique opportunities to foster learning through various modalities and enhance inter-professional interaction in the virtual space (Heuberger and Clark, 2019) utilizing a particular learning style preference.

Moreover, Lau and Gardner (2019) have substantially supported this in their findings revealing that the student's learning style would benefit teachers in maximizing the delivery of the lesson and the classroom activities through independent learning and collaborative learning. Other findings showed that using a single learning style with high visual and sensing learning styles can use 3D visualization instruction (Hung *et al*., 2019). On the contrary, learning style does not moderate knowledge map construction methods of learning scores, but learning style is a substantial moderator of knowledge map building methods on learning satisfaction (Shaw, 2019). Therefore, revealing students' learning style preferences empowers connectionism between the learner and the teacher. The teacher may utilize a single learning style in which the learners have the highest preference to unleash their optimum potentials such as skills, knowledge and rationality in decision-making.

Machine learning as a tool in predicting future information based on historical data can be used in determining students' learning style preferences. It is said that machine learning is a subset of artificial intelligence that aid computers to learn from historical data and make intelligent decisions. According to Nafea (2018), machine learning is flexible enough to cater to all students by using algorithms. Since the prediction and classification involve machine learning models and algorithms, learning styles and their patterns can be unfolded (Rasheed and Wahid, 2021).

The importance of unveiling the students' learning style is evident, and machine learning (ML) is also apparent in detecting learning styles. In the context of machine learning algorithms application, some studies have tried to develop models for learning style detection in e-learning systems and adaptive e-learning systems such as the use of data coming from online classes applying various classification algorithms like decision trees, support vector machine, k-nearest neighbors (KNN), K-means, Naive Bayes, linear discriminant analysis, random forest and logistic regression where results shown was limited and output not disclosed due to a non-disclosure agreement signed with the university (El Aissaoui *et al*., 2019; Rasheed and Wahid, 2021). By looking into the algorithms used, it is apparent that the datasets were integers and categorical numbers. On contrary, the J48 algorithm utilized a combination of text, characters and numbers (either categorical or continuous variables) and a text-based categorical dependent variable. Moreover, J48 is much simpler than those mentioned algorithms, like the random forest and with the same generated rule-based model. In addition, the J48 has many additional features including the accounting for missing values, decision tree pruning, continuous attribute value ranges, derivations of rules and others (Khanna, 2021). A study conducted using Felder-Silverman's learning style utilizing C4.5 (J48) resulted in an accuracy rate of 95.7% (Jena, 2018) which inspired this study to test using Kolb's learning style preferences. Other studies include utilization of NBTree classification algorithm in detecting learning style using the Felder-Silverman learning style for an e-learning system (Özpolat and Akar, 2009), Bayesian network algorithm in detecting the learning style of a student in a web-based education system (Garcia *et al*., 2007) and a study utilizing decision tree techniques in a personalized creativity learning system (PCLS) which is popular in e-learning system in detecting learning style (Lin *et al*., 2013). Even recent studies have been based on the learning style and adaptive e-learning of Truong (2016), who detected learning style using a hybrid model in an online learning process of Hasibuan and Nugroho (2016). Other works utilized learning style detection, predicated on cognitive learning, using the reinforcement approach (Balasubramanian and Anouncia, 2018) and learning management system (Sheeba and Krishnan, 2019). These studies focused on detecting learning styles in an e-learning environment or learning management system with different views and experiences in a face-to-face learning environment.

The limited information about disclosing these learning styles and linking them to the learners' daily activities remains prevalent in many schools. Specifically, in developing countries where teachers mainly build their courses reflecting on their teaching loads without knowing the type of learners, they have may not always fit students' different learning styles (El-Bishouty *et al.*, 2019). Identifying students' learning styles and modifying teaching styles and material accordingly are essential to delivering quality education. More research on learners' learning styles may be conducted in developing countries (Stander *et al.*, 2019). Therefore, unfolding the learners' learning styles is essential in preparing the type of pedagogy that the teacher will use along with the appropriate learning materials. What remains underscored is how to identify these learning styles faster than the manual identification procedure. Therefore, it is pragmatically clear that there is a need to design a systematic way of identifying learners' learning styles of Kolb's learning style preference. Anent to this premise, this study aimed to create a J48-based model in predicting students' learning style anchored on Kolb's learning style preferences and determine the evaluation results of the generated model utilizing confusion matrix, receiving operating characteristic (ROC) curve and Kappa statistics.

2. Methodology

This paper utilized a machine-learning algorithm to explore and discover important information from massive datasets and create a decision-support process to develop the appropriate intelligent system through a conditional rule statement model.

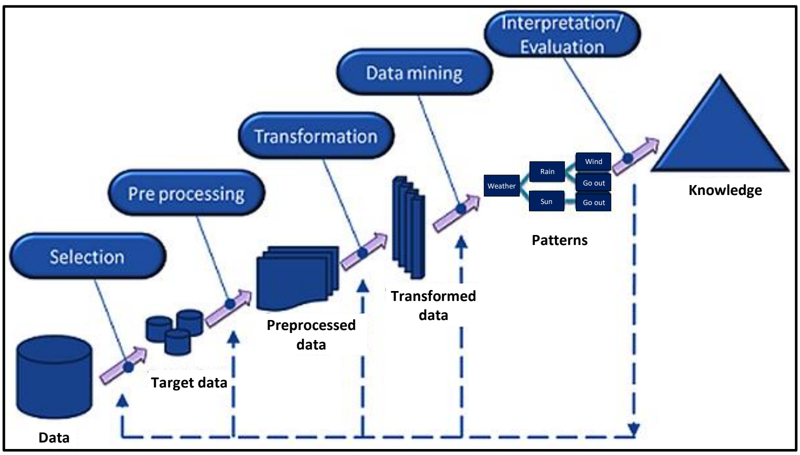

Figure 1. Data mining to knowledge discovery in databases process

Specifically, this paper underwent a rigorous process using knowledge discovery in databases (KDD) through data mining as Fayyad *et al.* (1996) proposed. Knowledge discovery is the nontrivial extraction of implicit, previously unknown and potentially useful information from data (Frawley et *al*., 1992; Fayyad, 2001). Figure 1 shows the process performed in this paper as discussed in detail below:

2.1 Step 1: Data Description

An instrument was prepared to collect data on respondents' basic profile and perceived learning style based on Kolb's learning style preference. Table 1 illustrates the variable definition used in this study.

Table 1. Variable definition in detecting learning style preferences

Code	Description	Value/type
Age	Age (value integer)	Ranging from 17 to 31
Sex	Sex (binary value)	0 – Female 1 – Male
FIM	Family income per month	1 – Under 7,890 2 – 7,890-15,780 3 – 15,780-31,560 4 – 31,560-78,900 5 – 78,900-118,350 6 – 118,350-157,800 7 – 157,800 and over
IH	Internet connectivity at home (binary value)	0 – No 1 – Yes
SIC	Other source of internet connectivity	1 – School free Wi-Fi 2 – Internet café 3 – Malls' free Wi-Fi 4 – Free mobile data 5 – Other
DCI	The technology used to connect the Internet	1 – Desktop computer 2 – Laptop computer 3 – Mobile phone 4 – Tablet or iPad
FIC	Frequency of internet connectivity per day	1 – Never 2 – 1 – 3 times 3 – 4 – 6 times 4 – 7 – 9 times 5 – More than 10 times
TS	Technology savvy (binary)	0 – No 1 – Yes
ACT	Activists (string)	Class { VSP – Very strong preference, SP – Strong preference,

Table 1 continued.

		MP – Moderate preference, LP – Low preference, VLP – Very low preference }

REF	Reflectors (string)	Class {
		VSP – Very strong preference,
		SP – Strong preference,
		MP – Moderate preference,
		LP – Low preference,
		VLP – Very low preference
		}

THEO	Theorists (string)	Class {
		VSP – Very strong preference,
		SP – Strong preference,
		MP – Moderate preference,
		LP – Low preference,
		VLP – Very low preference
		}

PRAG	Pragmatists (string)	Class {
		VSP – Very strong preference,
		SP – Strong preference,
		MP – Moderate preference,
		LP – Low preference,
		VLP – Very Low preference
		}

The instrument underwent two validation phases: the face validity and the reliability test using Cronbach alpha. Experts performed face validation in grammar and statistics to determine the extent to which a test was instinctively regarded as covering the concept it purported to measure. After the instrument was revised following the validity test, the reliability test was performed on 50 information technology (IT) students at another state university. The value for the Cronbach's alpha for the test was 0.837. After the validation of the questionnaire, the researcher encoded in Google Form and requested the faculty members of IT Unit in the university to distribute the link to the respondents and were asked to answer the survey questionnaire. The researcher selected the IT students in a state university as respondents in this study to determine the students' learning Styles. There were 462 IT students from the first to the fourth year. However, only 408 students responded to the survey. The data was collected on November 2019 before the COVID-19 pandemic in preparation for developing instructional materials (IMs) and modules for incoming second semester of school year 2019-2020. After the data collection, the researcher selected the classes in detecting and predicting the outcome of the predicted class such as activist, reflector, theorist and pragmatist learner.

2.2 Step 2: Data Pre-Processing

The data were pre-processed through data cleaning to establish data consistency. In this study, the researcher extracted the data from Google Forms through its generated worksheet file that can be read via Microsoft Excel. The data were checked several times to show that it was in accordance with the required information to be processed in a machine learning-based algorithm. In this stage, the researcher established that all 408 datasets qualified for the next stage.

2.3 Step 3: Data Transformation

After the data pre-processing, data transformation followed. This study utilized one hot encoding (OHE) since it is the most commonly used strategy due to its simplicity (Rodriguez *et al*., 2018). It is a process by which categorical variables are converted into a form that could be provided to ML algorithms to do a better job in prediction. In this stage, some values/types were transformed using OHE techniques such as the transformation of variable sex from word to binary value (0, 1), FIM from word to numbers such as (1, 2, 3, 4, 5, 6, 7), IH from word to binary value (0, 1) and among others (Table 1).

2.4 Step 4: Data Mining

In this study, the researcher utilized the Weka software for machine learning algorithm application (Hall *et al*., 2009). Weka is a software developed at the University of Waikato in New Zealand. Weka software is a collection of machine-learning algorithms for data mining tasks (Hall *et al.*, 2009). In this paper, to generate a tree-based conditional rule statement, the J48 algorithm was utilized. Ten cross-fold validation was used in the training set to validate and accurately predict and detect the learners’ learning style preferences.

Roiger (2017) defines data mining as the process of finding interesting structures in data. In this stage, to find hidden information from the dataset, the researcher used the J48 algorithm. The J48 algorithm is a tree induction algorithm that complies with the industry standard algorithms that can be successfully applied to more demanding problem domains (Sousa *et al*., 2004). The J48 algorithm procedure is as follows: 1) check whether all cases belong to the same class; then, the tree is a leaf and is labeled with that class;

2) for each attribute, calculate the information and information gain; lastly, 3) find the best splitting attribute.

2.5 Splitting Criteria

Entropy (Equation1), as cited by Caluza (2020), is a probabilistic measure of impurity (Heylighen and Josyln, 2001).

$$entropy(p_1, p_2, \ldots p_n) = -p_1 log p_1 - p_2 log p_2 \ldots - p_n log p_n \quad (1)$$

or

$$H(X) = -\sum_x p(x) log p(x)$$

where *p* is the value of the predictor variable divided by the sum of all predictor variables.

Information is a measure of reducing uncertainty or impurity (Caluza, 2020). To determine the best attribute for a specific node in the tree, information gain (IG) was used (Equation2).

$$IG\ (S, A) = Entropy\ (S) - Entropy\ (A) \quad (2)$$

Gain ratio (GR) is an alteration of information gain that reduces its bias on highly branching features (Caluza, 2020). It also solved the drawbacks of IG. Therefore, the information gain ratio is a ratio of IG and intrinsic information. Intrinsic information (Equation 3) represents the potential information generated by splitting the dataset into *v* partitions. Thus, the feature with the maximum gain ratio (Equation 4) was selected as the splitting feature.

$$IntrinsicInfo\ (D) = \sum_{j=1}^{v} \frac{|D_j|}{D} \cdot log_2\left(\frac{|D_j|}{D}\right) \quad (3)$$

$$GainRatio\ (S,A) = \frac{Gain\ (S,A)}{IntrinsicInfo\ (S,A)} \quad (4)$$

2.6 Interpretation or Evaluation

In interpreting the generated tree, the following were employed:

TP-rate or true positive rate, also known as sensitivity, measures the probability of correctly identifying actual positives (Zweig and Campbell, 1993; Kamil, 2015; Ekelund, 2017).

FP-rate or false positive rate is the proportion of all negatives that still yield positive test results (Zweig and Campbell, 1993; Lin *et al.*, 2015; Ekelund, 2017).

False-negative is when a negative result is wrong – meaning, a negative result should be categorized as positive (Chang *et al.*, 2006).

True-negative, known as specificity, is the ability of a test to correctly classify an individual (Parikh *et al*., 2008). It is calculated as the number of correct negative predictions divided by the total number of negatives.

Receiver operating characteristics curve, the TP-rate (sensitivity) is plotted in function of the FP-rate (100-specificity) for different cut-off points. Each point on the ROC curve denotes a sensitivity/specificity pair equivalent to a particular decision threshold. A test with perfect discrimination has a ROC curve that passes through the upper left corner (100% sensitivity; 100% specificity). Therefore, the nearer the ROC curve to the upper left corner, the higher is the test's overall accuracy (Zweig and Campbell, 1993). In support, the nearer the ROC value to 1, the better is sensitivity and specificity in the threshold, which also means the better the classification accuracy by class (Davis and Goadrich, 2006).

Confusion matrix was used to illustrate the correct classification and the misclassifications of learning style preferences. It is also known as an error matrix, which visualizes an algorithm's performance (Stehman, 1997). Anent to this, a confusion matrix table is used to define the performance of a classification algorithm (Singh *et al*., 2021). Thus, it provides the accuracy of the class. The following were the classes used to determine the learning style preferences in terms of activist, pragmatist, theorist and reflector learner: classes in the confusion matrix are represented by a, b, c, d and e, where a is the low preference (LP), b is the moderate preference (MP), c is the strong preference (SP), d is the very low preference (VLP), and e is the very strong preference (VSP).

Kappa statistics is a metric that compares an observed accuracy with an expected accuracy (random chance). The kappa statistic is applied not just to evaluate a single classifier but also classifiers. Alternatively, there is no standardized interpretation of the kappa statistics (Twain, 2014). In this paper, the work of Fleiss and Cohen (1973) was adopted in interpreting the Kappa statistics (κ) with the following scales: 0.81-1.00 (almost perfect), 0.61-.80 (substantial), 0.41-0.60 (moderate), 0.21-0.40 (fair), 0.01-0.20 (slight) and less than 0.0 (poor or no agreement) (Fleiss and Cohen, 1973; Landis and Koch, 1977; Twain, 2014).

3. Results and Discussion

This paper adopted the prediction of the learning style preference based on Kolb's Learning Style Preference processes (Kolb's Learning Style Questionnaire, n.d.). The decision tree models were the results of the computer simulation based on the given variables and datasets from the respondents' responses. The conditional rule models in detecting the learning style preferences are shown in figures through visualization using the J48 pruned tree. These trees are shown in Figures 2, 3, 4 and 5 for detecting the activist, reflector, theorist and pragmatist learners, respectively. These conditional rule models are now the basis for designing a system or application to determine the learner's learning style preference based on their characteristics. These conditional rule statements imitate condition reasoning for decision-making. When deciding, conditional reasoning plays an important role, and among those strategies in information technology is the "what if analysis." These If-Then-Else statements have shown significant impact and importance in programming. Thus, conditional rule statements such as the results of this study would help develop a decision support system in detecting the learning style preference of the learner.

The summary of the evaluation of detecting learning style preference is shown in Table 2. It revealed that in terms of correct classification, the theorist learning style preference had the highest correct classified instances of 343 out of 408 total instances. The reflector learner had 310 correct classifications, the pragmatist learner with 294 correct classifications and activist learner with 278 correct classifications. Results implied that the respondents like to analyze and synthesize. They are keen on trying out ideas, theories and techniques (Department of Health and Aged Care, 2004) in real-life situations, problem-solving exercises and case analysis (Sarabdeen, 2013). These characteristics are required in the IT industries as programmers, systems analysts, software designers, database analysts and the like. These results were supported by comparing the observed accuracy with an expected accuracy, also known as the Kappa statistics. It showed that the theorist learner (κ = 0.73), reflector learner (κ = 0.62) and pragmatist learner (κ = 0.61) had a substantial agreement, while the activist learner (κ = 0.59) had moderate agreement. Substantial agreement means a good agreement from the raters or respondents since it was within 0.60-0.80; conversely, a moderate agreement indicates an inadequate agreement from the raters or respondents since it was within the range of 0.41-0.60. It is important to understand the meaning of how raters agree or the extent to which the data collected in the study are correct representations of the variables measured (McHugh, 2012). This result revealed that correctly classified instances to inter-rater reliability showed an acceptable model. In support, the ROC curve, as presented in the previous discussion, establishes accuracy in the test. This paper's ROC results of the different learning style preferences are shown in Table 3. The table shows that the learner's style preference typified a theorist learner with a ROC curve weighted average value of 0.96 and with the highest value, as very strong preference with a ROC curve value of 0.99; this was followed by the activist learner with 0.91, the pragmatist learner with 0.90 and reflector learner with 0.88 ROC curve weighted average value.

Table 2. Summary of the evaluation of detecting learning style preferences

Summary	Activist	Reflector	Theorist	Pragmatist
Correct classified instances	278	310	343	294
Incorrectly classified instances	130	98	65	114
Kappa statistics	0.59	0.62	0.73	0.61
Total number of instances	408	408	408	408

Table 3. Summary of the ROC curve of learning style preferences

Strength of learning preferences	Activist	Reflector	Theorist	Pragmatist
Very strong preference (VSP)	0.90	0.86	0.99	0.93
Strong preference (SP)	0.92	0.91	0.95	0.92
Moderate preference (MP)	0.91	0.88	0.95	0.86
Low preference (LP)	0.93	0.88	0.96	0.92
Very low preference (VLP)	0.89	0.85	0.94	0.89
Weighted average	0.91	0.88	0.96	0.90

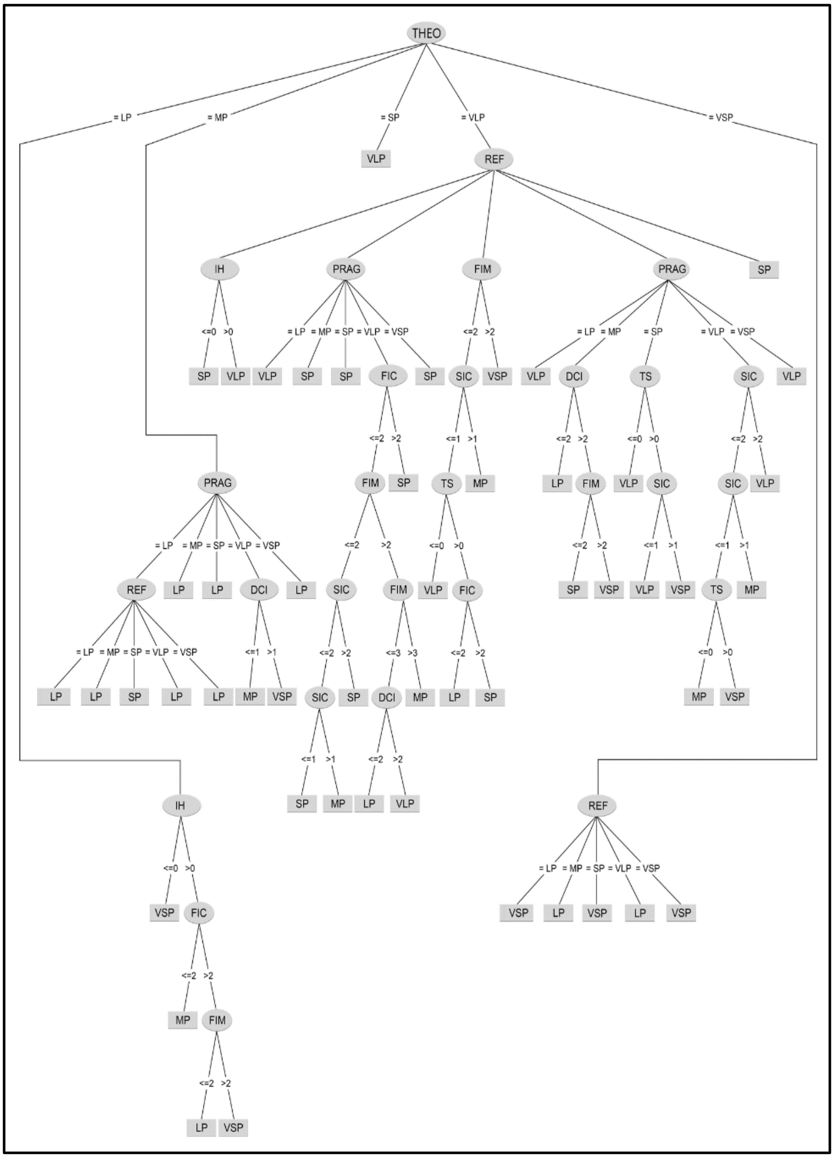

Figure 2. J48 pruned tree in detecting activist learner

Based on the result, the theorist learner had the highest correct classification compared with other types of learners and was supported with the highest strength of learning preferences among the respondents with 99% response and interpreted as a very strong preference. Therefore, the result implies that Information Technology Students should be given activities where they perform real and complex problems, think rationally and apply logical and critical thinking skills in analyzing and providing practical yet useful solutions to specific problems. Teachers should prepare instructional materials utilizing this kind of problem-solving activities and exercises to enhance their knowledge and critical thinking skills further. Theorist learners like to analyze and synthesize (Department of Health and Aged Care, 2004). They assimilate and convert disparate facts and observations into coherent, logical theories: their philosophy prizes rationally and logic above all. Theorist learners are intellectual, rational and objective (Furnham *et al.*, 1999), consider all alternatives and make conclusions from their experiences. These individuals usually attempt to fit their observations into a logical model or theory and learn best when required to understand complex problems (Shaw and Marlow, 1999).

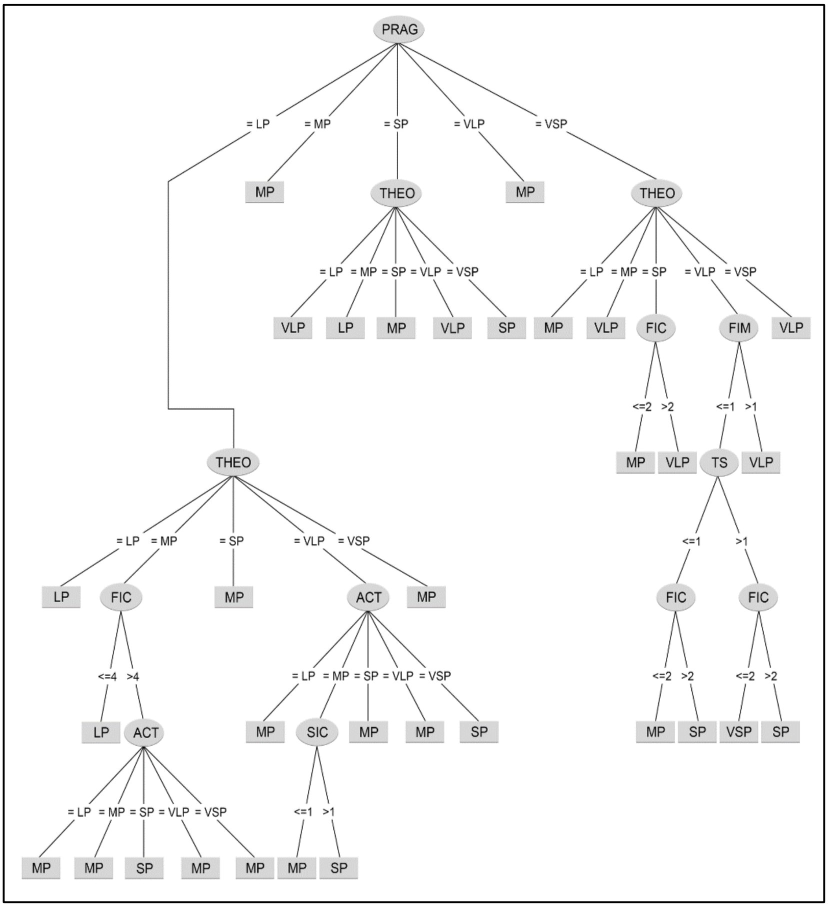

Figure 3. J48 pruned tree in detecting reflector learner

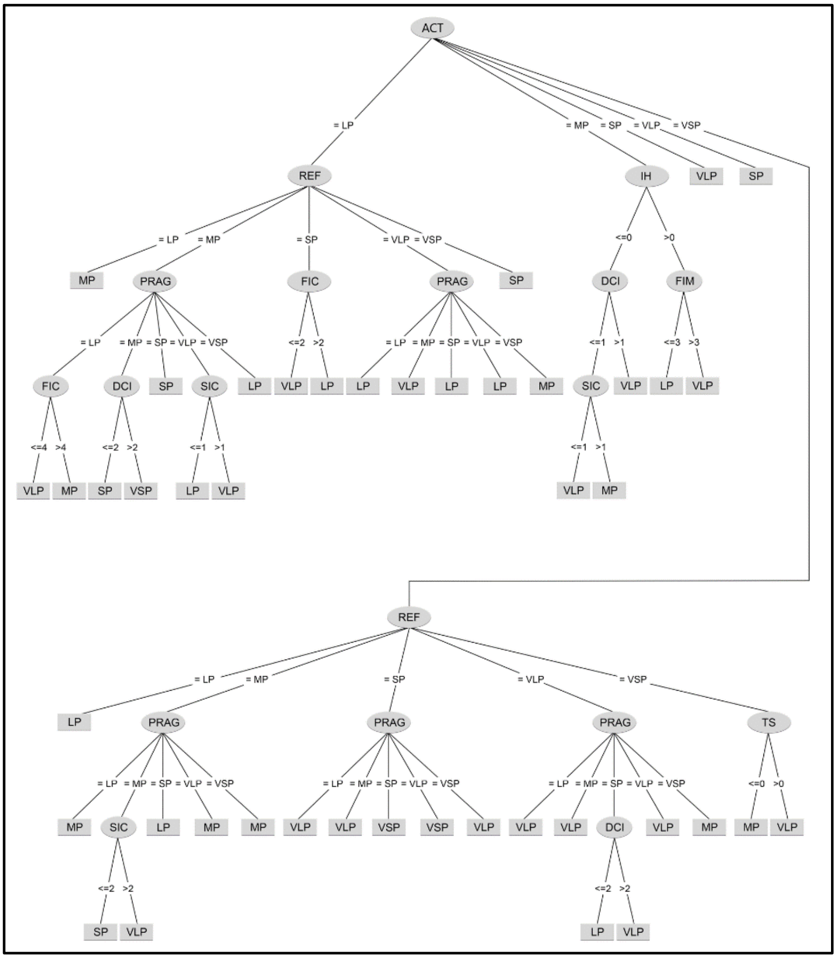

Figure 4. J48 pruned tree in detecting theorist learner

The confusion matrix by class in detecting activist learners is shown in Table 4 and interpreted as the following:

Fifty-three instances were correctly classified as low preference, while two, three, four and 12 were classified as moderate, strong, very low and very strong preference, respectively, resulting in 21 misclassifications.

Twenty-two instances were correctly classified as moderate preference. On the contrary, one, three and three were classified as low, very low and very strong preference, respectively, resulting in seven misclassification of instances.

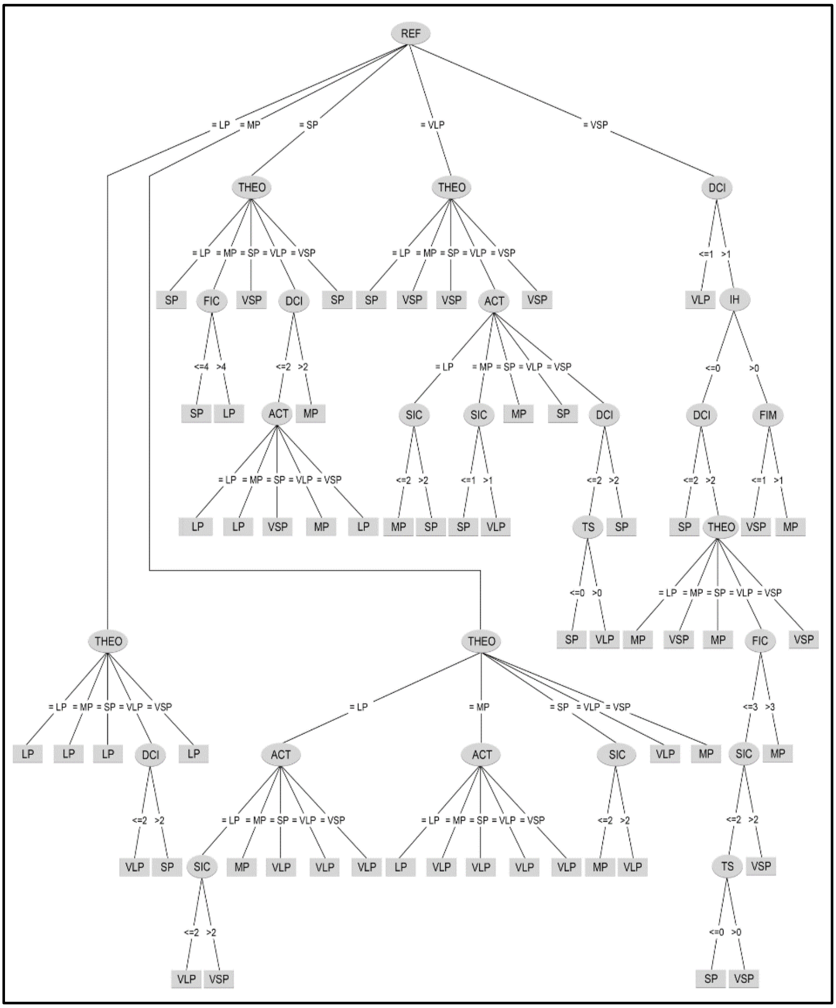

Figure 5. J48 pruned tree in detecting pragmatist learner

Seventy-five instances were correctly classified as strong preference. Four, 13, 23 and 17 were low, moderate, very low and very strong preference, respectively, resulting in 57 misclassifications.

Forty-one instances were correctly classified as very low preference, while five, seven, three and 10 were classified as low, moderate, strong and very strong preference, respectively, resulting in 25 misclassifications.

Eighty-seven instances were correctly classified as very strong preference, while 14, four, one and one were classified as low, moderate, strong and very low preference, respectively, resulting in 20 misclassifications.

Table 4. Confusion matrix by class in detecting activist learner

a	b	c	d	e	←Classified as
53	1	4	5	14	a = LP
2	22	13	7	4	b = MP
3	0	75	3	1	c = SP
4	3	23	41	1	d = VLP
12	3	17	10	87	e = VSP

The confusion matrix by class in detecting reflector learner is shown in Table 5 and interpreted as:

Seven instances were correctly classified as low preference, while one as strong preference and one as very low preference resulting in two misclassifications.

A total of 174 instances were correctly classified as moderate preference, while four, 15, 31 and 12 were classified as low preference, strong preference, very low preference and very strong preference, respectively, resulting in 62 misclassifications.

Table 5. Confusion Matrix by class in detecting reflector learner

a	b	c	d	e	←Classified as
7	4	0	4	0	a = LP
0	174	2	9	0	b = MP
1	15	45	7	1	c = SP
1	31	2	77	0	d = VLP
0	12	0	9	7	e = VSP

Forty-five instances were correctly classified as strong preference, while two as moderate preference and two as very low preference resulting in four misclassifications.

Seventy-seven instances were correctly classified as very low preference, while four as low preference, nine as moderate preference, seven as strong preference and nine as very strong preference resulting in 29 misclassifications.

Seven instances were correctly classified as very strong preference, while there was one as strong preference resulting in one misclassification.

The confusion matrix by class in detecting theorist learners is indicated in Table 6 and interpreted as:

Thirty-one instances were correctly classified as low preference, while one as moderate preference, five as strong preference, eight as very low preference and one as very strong preference resulting in 15 misclassifications.

Thirty-two instances were correctly classified as moderate preference, while four as low preference, four as strong preference, nine as very low preference and one as very strong preference resulting in 18 misclassifications.

Nineteen instances were correctly classified as strong preference, while one as low preference, two as very low preference and one as very strong preference resulting in four misclassifications.

Table 6. Confusion matrix by class in detecting theorist learner

a	b	c	d	e	←Classified as
31	4	1	6	2	a = LP
1	32	0	9	0	b = MP
5	4	19	6	2	c = SP
8	9	2	227	0	d = VLP
1	1	1	3	34	e = VSP

A total of 227 instances were correctly classified as very low preference, while six as low preference, nine as moderate preference, six as strong preference and three as very strong preference resulting in 24 misclassifications.

Thirty-four instances were correctly classified as very strong preference, while two as low preference and two as strong preference resulting in four misclassifications.

The confusion matrix by class in detecting pragmatist learners is exhibited in Table 7 and interpreted as:

Seventeen instances are correctly classified as low preference, while one as moderate preference and one as strong preference resulting in two misclassifications.

Thirty-nine instances were correctly classified as moderate preference, while one as low preference, 13 as strong preference, three as very strong preference and five as very strong preference resulting in 22 misclassifications.

One hundred six instances were correctly classified as strong preference, while six as moderate preference, ten as very low preference and seven as very strong preference resulting in 23 misclassifications.

One hundred ten instances were correctly classified as very low preference, while 15 as low preference, 26 as moderate preference, 12 as strong preference and five (5) as very strong preference resulting in 58 misclassifications.

Twenty-two instances were correctly classified as very strong preference, while three as moderate preference, four as strong preference and two as very low preference resulting in nine misclassifications.

Table 7. Confusion matrix by class in detecting pragmatist learner

a	b	c	d	e	←Classified as
17	1	0	15	0	a = LP
1	39	6	26	3	b = MP
1	13	106	12	4	c = SP
0	3	10	110	2	d = VLP
0	5	7	5	22	e = VSP

4. Conclusion and Recommendation

Identifying the students' learning styles is an essential and delicate endeavor in a teaching and learning environment. Therefore, understanding and identifying the learning style preferences is significant so that knowledge transfer is smooth and enjoyable. In this connection, the need for a more systematic understanding of the student's learning style was developed anchored on Kolb's student learning style preference utilizing the J48 algorithm. A J48 pruned decision tree model was developed and tested using 10-cross fold validation to predict the students' learning styles (activist, reflector, theorist and pragmatist). By using this model, it will be easier to identify and implement in detecting students' learning style preferences and teachers have to embrace it regardless of the diverse students for them to provide the best learning experiences for the students. Additionally, in the realm of teaching and learning, teachers need to be flexible or adaptable to the type of their learner's learning styles because learning styles are a life-long process that changes over time. As this research is limited in understanding the phenomenon, adding more variables and conducting a larger sample of the same type of learners is recommended.

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