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Integrated Stochastic and Literate Based Driven Approaches in Learning Style Identification for Personalized E-Learning Purpose

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***Abstract*— This paper presents integrated stochastic and literate based driven approaches in learning style identification for personalized e-learning purpose. Shifting a paradigm in education from teacher learning to student learning center has encouraged that learning should follow and tailor learners' characteristics in the form of personalized e-learning. There are several aspects to describe a condition of learners such as prior knowledge, learning goals, learning styles, cognitive ability, learning interest, and motivation. Even though, in many studies of the personalized e-learning, the learning style plays a significant role. In terms of e-learning, implementing several methods for identifying learner style becomes more challenging. Artificial intelligence and machine learning method give good accuracy, but they still have some issues in computation. Additionally, the stationary method is very hard to represent non-deterministic and dynamic data. Therefore, this research proposes the learning style identification by integrating stochastic and literate based driven approaches. Hidden Markov Model (HMM) and the Naïve Bayes as the Stochastic Approach have been implemented. Subsequently, learner behavior as the literate based data is used to get hints during accessing the learning objects. The proposed model has been implemented to VARK learning style. The accuracy is calculated by comparing the model results with the questionnaire results. When Using the HMM, the proposed model gives accuracy in the range of 95% up to 96.67%. Additionally, when using the Naïve Bayes; the accuracy is 93.33%. The results give better accuracy compared to previous studies. In conclusion, the proposed model is promising for modeling learner style in personalized e-learning.**

***Keywords*— Literate based driven; learning style; personalized e-learning; stochastic approach; VARK learning style.**

I. Introduction

The concept of personalization is the process of changing or adding something to the object so that it matches the needs of an individual. In the context of an e-learning environment, the personalization has become a crucial topic as the learning process does not fit all individuals who have different preferences, styles, and interests. Therefore, it becomes very important if an e-learning system can provide materials, paths and learning approaches meeting the needs and expectations of the learners [1]. The personalization of e-learning is defined as learning strategies that facilitate and support individual learning where each user has a path of learning needs and services according to his/her needs. It is essential that an e-learning system can be supported by personalization feature [2].

The process of adaptation in personalized e-learning consists of three processes, namely: Selection, Sequencing, and Presentation [3]. The other study presents five types of personalization: learning structure, learning model, learning scenario, content selection, and portfolio based assessment [4].

The adaptation of the personalized e-learning is based on the personalization components in the form of parameters, conditions, and contexts that describe the characteristics of the learners. These characteristics are obtained by a series of surveys that are inputted into e-learning as well as from data collected during the interaction of the learners with the e-learning. The components of the personalization are used individually or in a combination of several components tailored to the system requirements. From many of these components, an element that is often used plays an important role in the model of the personalized e-learning is the use of a learning style. It gave positive impact to successful learning management system [5]. The learning style, as part of learners' personality of the users' mode, becomes a critical part of many studies of the personalized e-learning. The learning can represent the characteristic learner [6]. It is one of the essential components in the learner model of the personalized e-learning [7].

The learner model represents the characteristics of the learners. It consists of learners' profiles and classification conditions based on their learning style. Classification refers to data inputted / obtained from a series of questionnaires and logs of learners' data when interacting with e-learning. The data are stored in a database that is identified through a process / method of computing. Furthermore, the detected learning style of the learner is used as the context in the personalized learning.

Research related to the identification of learning style is mostly conducted to improve the effectiveness and performance of learning [8]–[10]. However, the approach is less efficient because it is done by performing a series of questionnaires and finding inconsistencies between the results of users' behavior when interacting with e-learning. In general, the identification of the learning style can be done through a data-driven method and literate based driven method [11][12]. The data-driven process is done by transforming the questionnaires and using the sample data sets to build learner models [12]. The literate based driven uses user's behavior as it gives a clue of learning preference when interacting with e-learning [11]. Mostly, the data-driven approach uses the artificial intelligence and the data mining method such as support vector machine [13], k-means [14], fuzzy decision tree [15], and several computational intelligence algorithms [16]. On the other hand, the literate based approach is driven using a simple rule-based to make the process of computational for identification of the learning style [17].

Both of the data-driven and literate based driven approaches have advantages and limitations. For example, using the data-driven method with sufficient datasets and methods is appropriate and relatively accurate for identification the learning style. However, common algorithms are very complex with a large data, so that the burden is in the process of computation. The advantage of literate based driven is that it is simple in the process of computation, even though it is only suitable for measuring the data that are stationary and deterministic. Whereas on the learning style, it is often found things that are dynamic, non-deterministic, and non-stationary [18]. The stochastic approach gives the high accuracy, even it is implemented in noisy environment [19]. Therefore, this study integrated the stochastic approach and literate based data for learner style identification. The Hidden Markov Model (HMM) and the Naïve Bayes as the compared stochastic method are implemented in the proposed model. Many studies show that the methods are very popular and often used in the personalized e-learning modeling that uses a learning style [20]. The intensity of the learner during interaction with e-learning such as duration and frequency to visit particular learning material are observed as data for identification [21]–[23].

II. MATERIAL AND METHOD

A. Hidden Markov Model

The Hidden Markov Model (HMM) is an extension of the Markov chain in which its state cannot be observed directly (hidden), but it can only be observed through a set of other observations. A Markov chain is a mathematical technique used for modeling various systems and business processes. This technique can be used for estimation and prediction.

The HMM is a statistical model which the modeled system is assumed as a Markov process with states that are not observed. It can be considered as a simple Bayesian network. The Bayesian network as the stochastic approach would be the best method to deal with the dynamic condition, irregularity and stated scientific glitches. It also has been proven in the area of clinical expert systems, artificial intelligence, and pattern recognition [24]. Three particular problems can be solved by the HMM methods: Evaluation, Inference, and Learning. The evaluation problem can be solved using forward and backward algorithms, inference problem with Viterbi algorithm, whereas learning problem uses Baum-Welch algorithm. The representation parameters of the HMM are presented in Figure 1.

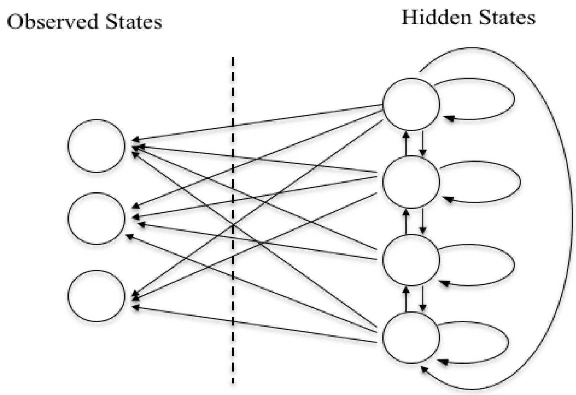

Fig. 1 Representation parameters of HMM

B. Learning Style

Learning style refers to a range of several theories that aim to figure out the diversity of individual learning. These theories propose that all learners can be classified according to their style of learning, although the various theories present different views on how the style should be defined and categorized [25]. A simple concept is that individuals differ in how they learn. Learning style can determine how a learning material should be presented. Some learners tend to think in general view; conversely other learners prefer to learn in detail. Some of them incline to work on projects or cases actively, while others prefer to listen passively from the teacher. By considering insights into different learning styles, it offers a learning situation that tailors individuals' needs.

There are several models for defining and measuring the proposed learning style. Kolb's model proposes that learners can be classified into convergers, divergers, assimilators, and accommodators [26]. Honey and Mumford's model presents learning style into activist, reflector, theorist and pragmatist [27]. Felder and Silverman's model categorizes learning style into intuitive/sensitive, global/sequential, visual/verbal, inductive/deductive and active/reflective [28]. According to the Dunn and Dunn's model, learning style is divided into five major elements namely stimuli: environmental, emotional, sociological, psychological, and physiological [29]. Neil Fleming proposes VARK model that learning style is classified into visual, auditory, read/write, and kinaesthetic [30].

C. The Proposed Model

The proposed model in this study involves the stochastic approach and literate based data. The stochastic approach is conducted as a method to identify the learning style of the learners. The method uses literate based data through acquired attributes during learner interaction with e-learning. The general process of the proposed model is shown in Figure 2. Once the learner logs in to e-learning, they have to fill in a learning style questionnaire. In the following process, they will face several learning objects associated with a certain learning style. Learner behavior during interaction with the learning objects will be recorded as the attributes and stored in the system.

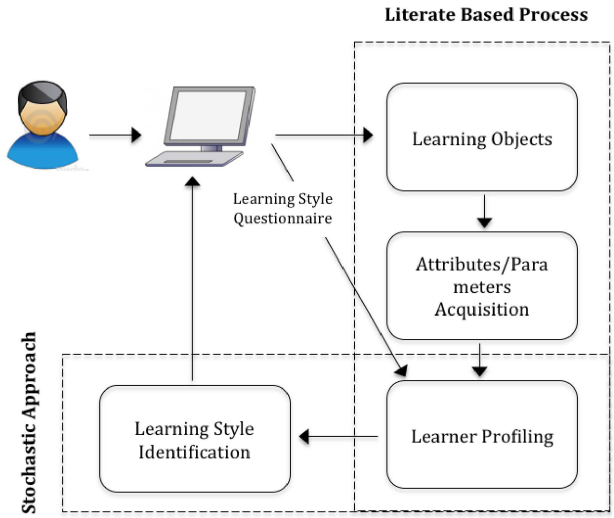

Fig. 2 The proposed model

This study uses two attributes as the observed parameters, namely duration and frequency of visit to certain learning objects. Regarding to VARK learning style that belongs to Visual, Auditory, Read, and Kinesthetic, every learner will have a profile consisting of tMV, tMA, tMR, tMR, fMV, fMA, fMR, fMK, and LS attributes. The tMV, tMA, tMR, and tMK are time duration when access a certain VARK learning object, whereas the fMV, fMA, fMR, and fMK are frequency to visit the certain VARK learning style. LS is learning style from the learning questionnaire (http://vark-learn.com/the-vark-questionnaire/). Based on the learner profile, the next process is to identify the VARK learning style using stochastic approach.

As mentioned in the proposed model, the learner model proposed in this study is based on the VARK (Visual, Auditory / Aural, Read / Write, Kinesthetic) learning style, stochastic processes, as well as the literature based data through intensity-based learning. The VARK model gives a clear and comprehensive picture of the learning style, time-efficient, and simply worded [31]. Additionally, it also is easy to implement it in a learning process [32]–[34].

The stochastic approach using the HMM is done according to the following considerations:

1. Although the tendency of a person's learning style converges on certain conditions, it still has the possibility to change [28].
2. The HMM is a manifestation of the Bayesian network method (simple dynamic Bayesian network), making it very efficient regarding computing, but it is reliable in the process of evaluation, inference, and learning [35]–[37].

The intensity of learning is used as observation probability matrices (emission matrices) that can provide an explicit description. It is observed through the following two parameters: (i) the length of time learning the specific types of learning materials; (ii) the frequency of visits to a particular kind of learning material. As a case of using the HMM approach, the conditions (states) involved in the model consists of hidden states and observed states. The Hidden state is a condition to be detected, the condition of one's learning style through the HMM approach. While the observed state is a condition that is recorded and subsequently in computing to infer and detect hidden conditions. The representation parameters of the proposed learner model are presented in Figure 3.

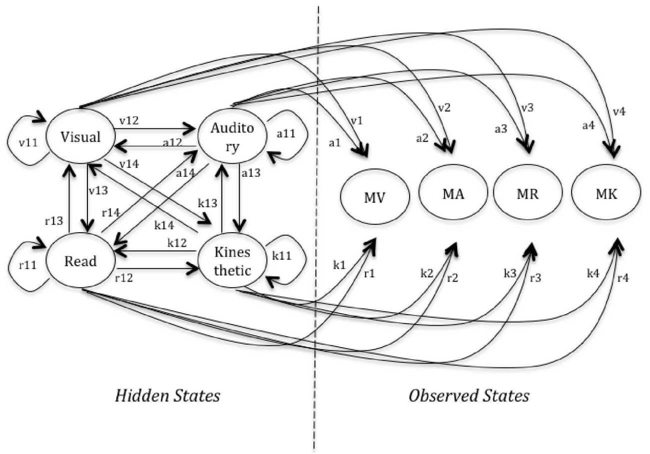

Fig. 3 Representation parameters of the proposed learner model

In the HMM Δ must be determined by five parameters involving in the process of computing which include the states to be detected (S), states that are observed (O), transition probability matrices (A), the observation probability matrices (B), and the initial value of the distribution state probability (S0) [38]. So, Δ = (S, O, A, B, S0). The following is the detailed explanation of the parameters involving in the proposed model:

1. S is the set consisting of the states of a person's learning style. S = {Visual, Auditory / Aural, Read / Write, Kinesthetic}.
2. O is the set consisting of a sequence of the observed state taken from learning materials associated with a particular learning style. MV is learning materials attributes associated with the Visual type. MA associated with Auditory / Aural. MR associated with Read / Write, while MK associated with Kinesthetic. O is determined by duration and frequency visit to the particular learning material.

3. A is transition probability matrices contains the probability of transition from one learning style to other learning styles.
   a. $v1i$ determines the probability of the transition from visual conditions to other conditions on the set S, where $\sum_{\mathrm{i}}^{\mathrm{S}} v1i = 1$.
   b. $a1i$ determines the probability of the transition from auditory conditions to others conditions on the set S, where $\sum_{\mathrm{i}}^{\mathrm{S}} a1i = 1$.
   c. $r1i$ determines the probability of the transition from read conditions to other conditions on the set S, where $\sum_{\mathrm{i}}^{\mathrm{S}} r1i = 1$.
   d. $k1i$ determines the probability of the transition from kinesthetic conditions to other conditions on the set S, where $\sum_{\mathrm{i}}^{\mathrm{S}} k1i = 1$.

$$A = \begin{bmatrix} vv & va & vr & vk \\ av & aa & ar & ak \\ rv & ra & rr & rk \\ kv & ka & kr & kk \end{bmatrix}$$

$$= \begin{bmatrix} v11 & v12 & v13 & v14 \\ a11 & a12 & a13 & a14 \\ r11 & r12 & r13 & r14 \\ k11 & k12 & k13 & k14 \end{bmatrix} \quad (1)$$

4. B is observation probability matrice that provides the probability of learning materials that are visited by a learner with a particular learning style.
   a. *vj* states probability of a visited learning material with the visual learning style state, where $\sum_{j}^{O} vj = 1$.
   b. *aj* states probability of a visited learning material with the auditory learning style state, where $\sum_{j}^{O} aj = 1$.
   c. *rj* states probability of a visited learning material with the read learning style state, where $\sum_{j}^{O} rj = 1$.
   d. *kj* states probability of a visited learning material with the kinesthetic learning style state, where $\sum_{j}^{O} kj = 1$.

$$B = \begin{bmatrix} vMV & vMA & vMR & vMK \\ aMV & aMA & aMR & aMK \\ rMV & rMA & rMR & rMK \\ kMV & kMA & kMR & kMK \end{bmatrix}$$

$$= \begin{bmatrix} v1 & v2 & v3 & v4 \\ a1 & a2 & a3 & a4 \\ r1 & r2 & r3 & r4 \\ k1 & k2 & k3 & k4 \end{bmatrix} \quad (2)$$

5. S0 is the set that contains the initial value of the distribution of learner probability of the learning styles. The initial value can be obtained through a questionnaire or filled with a value that is distributed evenly, for example, in this study S0 = {Visual, Auditory / Aural, Read / Write, Kinesthetic} = {0.25, 0.25, 0.25, 0.25}. This value changes dynamically according to the person's behavior when interacting with the e-learning that identifies learning style.

D. *Research Methodology*

To validate the accuracy and suitability of the proposed model, it was conducted a series of activities in the form of the model implementation in e-learning, observation, data collection, and data analysis. The proposed model was implemented to 60 students of the Politeknik Caltex Riau who took a course on project management. Observations had been conducted ten weeks involving five courses that taught topics with each topic was supported by learning materials as shown in Table I.

Each topic of the learning materials had been stored in e-learning database for two weeks and had been set that the learning material could only be accessed by students during interact with e-learning. This scenario was conducted to measure and record the intensity of learning as observation parameters in the proposed model. They are the length (duration) of a student in accessing certain types of learning materials and the frequency of a student in accessing certain types of learning materials. The data was obtained through the server logs available on e-learning. The first parameter was measured in minutes while the second parameter was measured by how many times a student accessed a particular learning material.

TABLE I.
LEARNING MATERIALS ASSOCIATED WITH THE VARK LEARNING STYLE

Type of Learning Materials	The VARK Learning Style
Video/Picture	Visual
Lecture (Monolog)	Auditory
Text (Slide, e-book)	Read
Instruction sheet, exercise	Kinesthetic

Subsequently, the proposed model was tested three times using parameter duration visit, frequency visit, and combination duration-frequency visit. The HMM implementation using Viterbi algorithm used the following parameters:

1. S = {V, A, R, K}
2. O = {o1, o2, o3, o4, o5}, oi ε {MV, MA, MR, MK}
3. Transition probability matrices A was obtained by conducting two times of the measurement of the learning style condition.

$$A = \begin{bmatrix} 0.5625 & 0.1875 & 0.0000 & 0.2500 \\ 0.0500 & 0.5500 & 0.1000 & 0.3000 \\ 0.0000 & 0.1250 & 0.5000 & 0.3750 \\ 0.0000 & 0.1250 & 0.0625 & 0.8125 \end{bmatrix}$$

4. The observation probability matric B was determined by calculating the conditional probability of the measurement of the learning styles with the results of the first observation.

$$B = \begin{bmatrix} 0.7500 & 0.0625 & 0.0000 & 0.1875 \\ 0.0500 & 0.6500 & 0.1000 & 0.2000 \\ 0.0000 & 0.1250 & 0.6250 & 0.2500 \\ 0.0000 & 0.1250 & 0.0625 & 0.8125 \end{bmatrix}$$

5. S0 = {Visual, Auditory / Aural, Read / Write, Kinesthetic} = {0.25, 0.25, 0.25, 0.25}.

Finally, the accuracy was measured by comparing the result of the proposed model with the results from the VARK questionnaire from all participants who were observed. The accuracy (P) shows percentage the fitness level between the model and the questionnaire result.

$$P = \frac{Number\ of\ matched\ learning\ style}{Number\ of\ respondent} s\ 100\% \qquad (3)$$

III. Results and Discussion

A. The Proposed Model Using Hidden Markov Model

As stated in the previous section, firstly the model was implemented using duration visit parameter. The model results show that 95% matches the questionnaire as shown in Table II.

TABLE II
LEARNING STYLE BASED ON DURATION VISIT

Student Number	Results		Student Number	Results	
	Proposed Model	**Questionnaire**		**Proposed Model**	**Questionnaire**
1	A	A	31	K	K
2	A	A	32	K	K
3	A	A	33	K	K
4	A	A	34	K	K
5	A	A	35	K	K
6	A	A	36	K	K
7	A	A	37	R	R
8	A	A	38	R	R
9	A	A	39	K	R
10	A	A	40	R	R
11	A	A	41	R	R
12	A	A	42	R	R
13	A	A	43	R	R
14	A	A	44	R	R
15	K	A	45	A	V
16	A	A	46	V	V
17	A	A	47	V	V
18	A	A	48	V	V
19	A	A	49	V	V
20	A	A	50	V	V
21	K	K	51	V	V
22	K	K	52	V	V
23	K	K	53	V	V
24	K	K	54	V	V
25	K	K	55	V	V
26	K	K	56	V	V
27	K	K	57	V	V
28	K	K	58	V	V
29	K	K	59	V	V
30	K	K	60	V	V

The results show that the learning styles of 57 students from the proposed model match the questionnaire results.

The second parameter, frequency visit, gives better results than the first one. It achieves 96.67% of the match with the questionnaire as shown in Table III. It is logic that the high-frequency visit represents more level of interest compared to the duration of the visit. Therefore, not all of the high duration of the visit to a particular learning material show level of interest. Moreover in e-learning situation, it is not guaranteed that someone is learning or not this particular learning material. Another possibility is that if the learners logged in to the e-learning and visited a certain learning material but they left it for several times, it could still be recorded as a high duration visit.

The data processing through a combination of the duration of the visit and the frequency of the visit gives the same percentage to the duration of the visit. It achieves 95% match between the proposed model and the questionnaire. In this research, the combination of the duration and frequency has the same weights in the model. It is interesting to investigate further by using a variety of weights. It can lead to identifying which parameter is dominant to achieve better results.

TABLE III
LEARNING STYLE BASED ON FREQUENCY VISIT

Student Number	Results		Student Number	Results	
	Proposed Model	**Questionnaire**		**Proposed Model**	**Questionnaire**
1	A	A	31	K	K
2	A	A	32	K	K
3	A	A	33	K	K
4	A	A	34	K	K
5	A	A	35	K	K
6	A	A	36	K	K
7	A	A	37	R	R
8	A	A	38	R	R
9	A	A	39	R	R
10	A	A	40	K	R
11	A	A	41	R	R
12	A	A	42	R	R
13	A	A	43	R	R
14	K	A	44	R	R
15	A	A	45	V	V
16	A	A	46	V	V
17	A	A	47	V	V
18	A	A	48	V	V
19	A	A	49	V	V
20	A	A	50	V	V
21	K	K	51	V	V
22	K	K	52	V	V
23	K	K	53	V	V
24	K	K	54	V	V
25	K	K	55	V	V
26	K	K	56	V	V
27	K	K	57	V	V
28	K	K	58	V	V
29	K	K	59	V	V
30	K	K	60	V	V

B. The Proposed Model Using Naïve Bayes

The Naïve Bayes method is the second stochastic approach implemented in the proposed model. It will give the compared results as a benchmark to identify learning style. The Naïve Bayes is a classification method using data training and data testing. In order to validate the determination of both of data, this study uses k-fold cross-validation technique. For instance, the description of cross-validation with k=5, is shown in Figure 4. While the identification result is shown in Table IV.

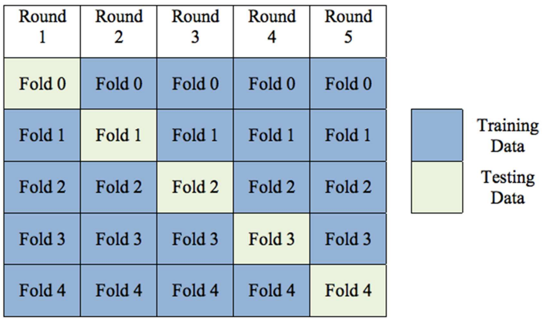

Fig. 4 k-fold cross validation with k=5

TABLE IV
LEARNING STYLE BASED ON FREQUENCY VISIT (NAÏVE BAYES)

Fold	#ID	Prediction	Questionnaire	Fold	#ID	Prediction	Questionnaire
0	15	V	V	2	31	V	V
0	16	K	K	2	34	K	K
0	18	A	A	2	41	A	A
0	2	K	K	2	44	A	A
0	21	R	R	2	55	R	R
0	25	A	R	2	59	V	V
0	28	R	K	3	12	V	V
0	38	K	K	3	13	K	K
0	42	A	A	3	24	R	A
0	49	K	K	3	32	K	K
0	58	A	A	3	35	A	A
0	6	V	V	3	43	A	A
1	10	V	V	3	45	A	A
1	11	R	R	3	48	R	R
1	19	A	A	3	50	A	A
1	22	K	K	3	51	A	A
1	3	V	V	3	54	A	A
1	37	R	R	3	8	K	K
1	39	A	A	4	0	K	K
1	4	R	R	4	14	V	V
1	40	A	A	4	20	V	V
1	5	V	V	4	30	K	K
1	56	V	V	4	33	K	K
1	57	A	A	4	36	K	K
2	1	K	K	4	46	A	A
2	17	V	V	4	47	R	R
2	23	V	V	4	52	A	A
2	26	A	A	4	53	K	K
2	27	V	A	4	7	V	V
2	29	V	V	4	9	V	V

Table V showed the confusion matrix and Cohen's Kappa value of the proposed model. The confusion matrix figured out about the accuracy level, while the Kappa value indicated the consistency and the reliability of the proposed model. The accuracy described prediction and questionnaire result is matched in 93.33%. The Kappa value is 0.909. It is more than 0.8. It indicated that the model is consistent and reliable.

The proposed model has been implemented by the stochastic approach and literate based data as observed parameter. The proposed model gives the accuracy in the range 95% - 96.67% using the HMM and 93.33% by using the Naïve Bayes. Even though, it was implemented in different learning style, it showed that the results are better relative to previous studies. The other literate based methods conducted by Dung et.al [17], the accuracy is 65.91% - 79.54%. The accuracy conducted by Graf et.al [11] is 73.33% - 79.33%, while the Simsek et.al [39] has 79.63% in accuracy.

TABLE V
CONFUSION MATRIX AND COHEN'S KAPPA VALUE

LS/Prediction (LS)	K	V	R	A
K	15	0	1	0
V	0	16	0	0
R	0	0	7	1
A	0	1	1	18
Accuracy	**93.33 %**			
Cohen's Kappa (K)	**0.909**			

By conducting this approach, the learning style is determined by the highest value of probability. Mostly, the results give a single learning style prediction for every student. In the fact, some learners may have a multi modal learning style.

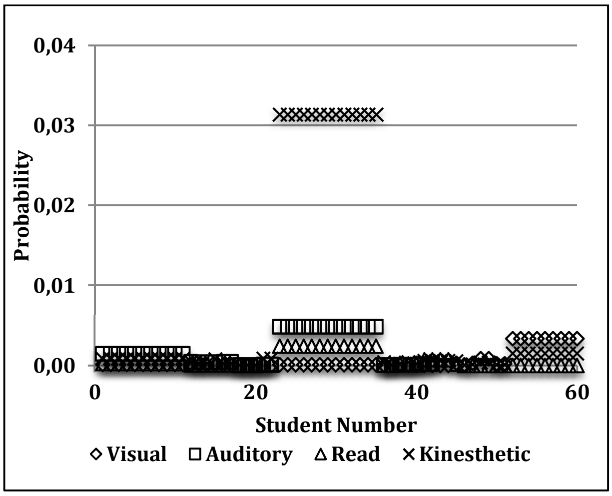

Fig. 5 Distribution probability value based on duration visit

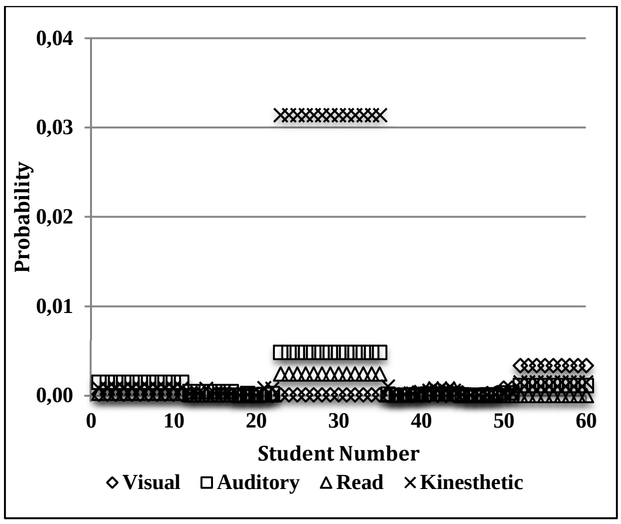

Fig. 6 Distribution probability value based on frequency visit

Figure 5 and Figure 6 show the distribution probability value of the learning style of each student. Visually, the students who identified kinesthetic learning style, they have significantly different in probability value with the others. Otherwise, some learners have quite same value of the distribution probability of the learning style. Using a statistical analysis, it can be tested that the situation is similar or not similar.

IV. Conclusion

An integrated stochastic and literate based driven approach in learning style identification has been presented in this paper. It has been given a further description of how the probability approach and learners' behavior were used for identifying the learners' learning styles. The HMM as the simple form of the Bayesian network method was implemented to deal with the complexity of the computation. As the compared result, the Naïve Bayes as the other stochastic approach was implemented to the proposed model. Furthermore, the proposed model gives the promising results that can be used for learning style identification.

The frequency visit parameter gives better results than the duration visit and combination both of them. Therefore, it can be interpreted that the high-frequency visit represents more levels of interest compared to the duration of the visit. It is possible if the learners log in to the e-learning and visit a certain learning material but they leave it for several times. However, it can still be recorded as a high duration visit.

The proposed model still identifies the single learning style of the learner. However, it is very possible that the learner can have more than a single learning style. In addition, the results show that the probability distribution of the learner style is similar. Finally, in the future research, by implementing more statistical approach, the model can identify learning styles not only for a single mode but also for multimodal learning styles.

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