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MODEL DETECTING LEARNING STYLES WITH ARTIFICIAL NEURAL NETWORK

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Abstract

Currently the detection of learning styles from the external aspect has not produced optimal results. This research tries to solve the problem by using an internal approach. The internal approach is one that derives from the personality of the learner. One of the personality traits that each learner possesses is prior knowledge. This research starts with the prior knowledge generation process using the Latent Semantic Indexing (LSI) method. LSI is a technique using Singular Value Decomposition (SVD) to find meaning in a sentence. LSI works to generate the prior knowledge of each learner. After the prior knowledge is raised, then one can predict learning style using the artificial neural network (ANN) method. The results of this study are more accurate than the results of detection conducted with an external approach.

Keywords – Detection learning style, Latent semantic indexing, Artificial neural network.

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1. Introduction

Current learning models have undergone changes from conventional learning to online learning models; these models are also known as e-learning, online learning, distance learning or web-based tutorials (Santosa, 2015). E-learning is used not only as a complement to learning but can also enrich conventional learning (Nugroho, 2013). In its application e-learning requires a personalization method, because the interaction between learners and teachers is very minimal. The various learning environments and background knowledge of each learner are also different.

One of the personalization methods that developed to be studied is detecting learners' learning style. In online learning, detection of learning style is very helpful. This is in line with Graff's opinion that learning style detection at the beginning of learning can help the learner to follow the learning more easily and improve the motivation to learn (Graf, Kinshuk, & Liu, 2008; Hasibuan & Nugroho, 2016). Among the learning styles involved are Kolb's Learning Style, Honey and Mumford, Felder-Silverman Learning Style Model and Visual, Aural, Read and Kinesthetic (VARK) (Kolb, 1984; Sangvigit, 2012).

Currently there are two approaches to learning style detection: these are conventional and automatic (Feldman, Monteserin & Amandi, 2015). Detection of conventional learning styles uses a questionnaire to detect learning styles. Each learning style has its own questionnaire that is able to represent the learning style. This is different from the automatic learning style detection model. The automatic learning style detection model works by way of learner interaction with the system. Current detection of automatic learning styles is divided into two approaches: data-driven and literature-based approach (Hasibuan, Nugroho, Santosa, & Kusumawardani, 2016; Nam, 2013).

The data-driven approach of learning style detection uses an artificial intelligence method to represent the questionnaire. Both approaches are based on the interaction of learners with the system, such as interaction with teaching materials, following discussion forums, online quizzes and online chats (Rita, Graf & Kinshuk, 2002; Nam, 2013; Hamtini, 2015; Hasibuan, Nugroho & Santosa, 2017). The approach can be classified as an external approach because the process involves learner interaction with the system. An external approach requires an online learning environment that has features capable of accommodating the learner's requirements. These include a wealth of learning management features, access speed and user-friendly interface.

The second approach is the internal approach, an approach derived from the personality and attitude of learners (Swinke, 2012). Approaching personality and attitude, according to Swinke, is something inherent in self-learners, such as memory (intelligent) and attitude of learners (attitude).

Intelligent dimensions are closely related to the ability of learners who can record, store and recall previous teaching materials. Meanwhile, the attitude dimension shows the attitude of learners who seek to have knowledge. Learner attitude can be divided into two categories, namely, able to increase motivation or demotivation. Both of the above dimensions relate to the prior knowledge of the learner.

This research builds a learning style detection model using an internal approach, i.e. prior knowledge. So far there are three methods to generate prior knowledge: these are brainstorming technique, cognitive map and Know-Want To Know-Learned (KWL) chart. These three methods have limitations such as inefficient use of time, accuracy of improper detection results and insufficient subjectivity. The solution to the generation problem is that this research uses Latent Semantic Indexing (LSI) to generate prior knowledge, and the result of this generation will predict learning style. Learning style prediction is done by using the Artificial Neural Network (ANN) method.

2. Related Literature and Study

2.1. Learning Style Model Detection

The learning style detection process can be divided into conventional and automatic forms (Hasibuan et al., 2017). Detection of conventional learning styles uses the questionnaire provided by each learning style. Questionnaires include Learning Style Instrument (LSI) for Kolb's learning style, Learning Style Questionnaire (LSQ) for Honey and Mumford style of learning, Index of Learning Style (ILS) for the Felder-Silverman learning style model and questionnaire for Visual, Aural, Read and Kinesthetic (VARK) learning style (Kolb, 1984; Honey & Mumford, 1992; Fleming & Mills, 1992; Felder & Silverman, 1988).

The detection of automatic learning style can be divided into two, namely data-driven and literature-based. Data-driven is the imitation of a questionnaire that leads to one of the artificial intelligence methods. Some research has been done with artificial intelligence i.e. Bayesian Network, Decision Tree and Neural Network, NB Tree algorithm, Hidden Markov and Genetic Algorithm (Özpolat & Akar, 2009; García, Amandi, Schiaffino & Campo, 2005; Cha, Kim, Park, Yoon, Jung & Lee, 2006; Yannibelli, Godoy & Amandi, 2006).

Patricio detected the learning style of Felder-Silverman Learning Style Model (FSLSM) using Bayesian Network performed by Patricio (García et al., 2005). The process of detection is only done to the three dimensions that have FSLSM learning style, that is, perception, processing and understanding. The results of the detection of learning styles performed by Patricio have a level of accuracy below 77%.

The same thing was done by Özpolat to detect the learning style of FSLSM by using NB Tree Classification (Özpolat & Akar, 2009). But in the study by Özpolat, the FSLSM learning style detection process used four dimensions: perception, processing, understanding and input. The results of the Özpolat study have an accuracy of below 73.3%.

Furthermore, a study by Cha et al. detected the FSLSM learning style using the Decision Tree and Hidden Markov approaches (Cha et al., 2006). Cha et al. used Decision Tree and Hidden Markov to detect FSLSM learning styles with four dimensions, namely, perception, processing, understanding and input. The results of Cha et al. showed detection accuracy below 83%, a value which is better than the studies by Özpolat and García.

Detection of the next learning style is Literature-Based; this work is based on learner visits to teaching materials. The learning system will retrieve the log data of the learner's visit to the teaching materials to determine the learning style (Rita et al., 2002; Nam, 2013; Popescu, Badica & Trigano, 2008). The data taken includes the length of visits to teaching materials and the pattern of visits.

Subsequent research by Hamtini has successfully detected the Visual Aural Kinethestic (VAK) learning style (Hamtini, 2015). This study captures learners' visits to learning materials (contents, case studies, examples, exercises and assessments) and assesses learner, visit and answers behaviours. The results of this VAK learning style detection yielded 52.78% accuracy.

Research by Ahmad et al. detected FSLSM learning style using a literature-based technique (Ahmad, Tasir, Kasim & Sahat, 2013). The dimensions of learning styles studied were the Active and Reactive dimensions. Both Active and Reactive dimensions work with Threshold and timing. The results of this study have an accuracy of 79.63%.

Another study was conducted by Graf et al., who detected FSLSM learning styles using a literature-based method (Graf, Viola & Kinshuk, 2007). This study uses the pattern of interaction of learners when accessing content, outline and examples. When a learner visits content, outline and example, this study measures the time and number of visits. The result of FSLSM learning style detection conducted by Graf et al. yielded 79.33% detection accuracy.

A study by Liyanage also detects FSLSM learning styles with a literature-based approach. Liyanage uses two methods: questionnaire and rule-based (Pitigala Liyanage, Gunawardena & Hirakawa, 2013). This study is similar to other literature-based research that uses interaction results of learners to outlines, contents, examples, self-assessments and exercises. The results of the use of an approach based on questionnaires and rules showed 77.5% accuracy.

A similar study to Liyanage's, that focused on detecting learning styles with the Learning Management System, was done by Abdullah, Alqahtani, Aljabri, Altowirgi and Fallatah (2015). Abdullah et al. (2015) detected all learning styles of FSLSM with an accuracy of up to 90% but only for processing dimensions.

Research on other literature-based learning style detection was done by Dung et al (Dung & Florea, 2012). Their research detects FSLSM learning style by constructing LMS POLCA. LMS POLCA provides learning materials accessible to learners. LMS POLCA provides a variety of teaching materials that every learner can access. Learning interaction process of this learning material will determine learning style of learners.

LMS POLCA will calculate the time the system provides compared with the actual time accessed by the learner. The results of this comparison will be the basis of decision making on learning styles. This study claims to have produced learning style detection accuracy up to 79.54%.

From the results of previous studies one can see some gaps that exist, as shown in Table 1.

	Özpolat & Akar	**García et al.**	**Ahmad et al.**	**Dung & Florea**	**Graf et al.**	**Cha et al.**	**Hamtini**	**Pitigala et al.**	**Abdullah et al.**
Year	2009	2005	2013	2012	2007	2006	2015	2013	2015
Sample	25 students	27 students	20 students	44 students	127 students	600 students	18 students	80 students	35 Students
Approach	Data Driven	Data Driven	Literature Based	Literature Based	Literature Based	Data Driven	Literature Based	Data Driven	Literature Based
Method	NB Tree Classification	Bayesian	Behaviours Pattern	Behaviour	Behaviours Pattern	Decision Tree dan Hidden Markov	Behavior	Data Mining J 48	Behaviour
Target Study	Engineering Education	AI	Interactive Multimedia	AII	Object Oriented Modelling	Multimedia	Pilot Elearning environment	Higher education	Data Structure
Assessment Method	Learning Model: ILS	BN Model: ILS	Behavior: ILS	Learning Object: ILS		Behaviour: ILS	Behaviour: ILS		Behaviour: ILS
Precision	67.7%	52%	75%-83%			Error rate <30%	52.78%	77.27%	76%
Dimension Ac/Ref Sen/Int Glo/Sec Vis/Ver	 70% 73.33% 73.33% 53%	 77% 63% 58% -	 75%	 72.73% 70.15% 79.54% 65.91%	 79.33%		 V A K	 70.89% 84.38% 91.25% 82.50%	

Table 1. Comparison of previous research

2.2. Latent Semantic Indexing

Latent Semantic Indexing (LSI) is a search method that works based on the similarity or meaning of a document. The document in question can be a sentence or text that has a hidden meaning (Retrieval, n.d.). This research works by making the learner's answer as input to be processed using LSI in order to gain meaning from the learner's answer. LSI is very effective to find the meaning of a document. In addition to the processing of documents that have a large capacity, LSI can provide accurate information.

Previous research has used LSI to find some traditions. Some of the traditions contained in a book can be found in search keywords with query-based searches. In this research, the search for the meaning of the hadith can be found as desired by the user (Nur, Tuan & Rahim, 2016).

2.3. Artificial Neural Network

Artificial Neural Network (ANN) is an artificial intelligence method that uses the concept of biological neural system. As for the workings of the biological nervous system, it starts with the nervous system receiving input or input from outside the system, then each nerve is connected with other nerves. Each nerve has a weight value. Input process that has the weights will be processed on the hidden layer and finally produce the appropriate output. Related research with ANN successfully predicted stock with 96% detection success.

Another prediction done by using ANN is to predict Iran's presidential election with 91% success. This research uses LSI to generate prior knowledge. The result of the assessment of prior knowledge will be used to predict learning styles.

3. Methodology Research

The Methodology Research used in this study is shown in Figure 1.

The first step done in this research is the process of generating prior knowledge. Priority of prior knowledge generation process uses only three methods. The three methods are Brainstorming, Know-Want To Know-Learned (KWL) Chart and Cognitive Map (Thi Thanh Dieu, 2015; Gouveia, 1974; Hasibuan et al, 2017). The constraints faced in previous prior knowledge generation process are that it is less effective, and very subjective because there is interaction and the process takes a long time. This study improves the previous constraint by using Latent Semantic Indexing (LSI) method. The architecture of the use of LSI method can be seen in Figure 2.

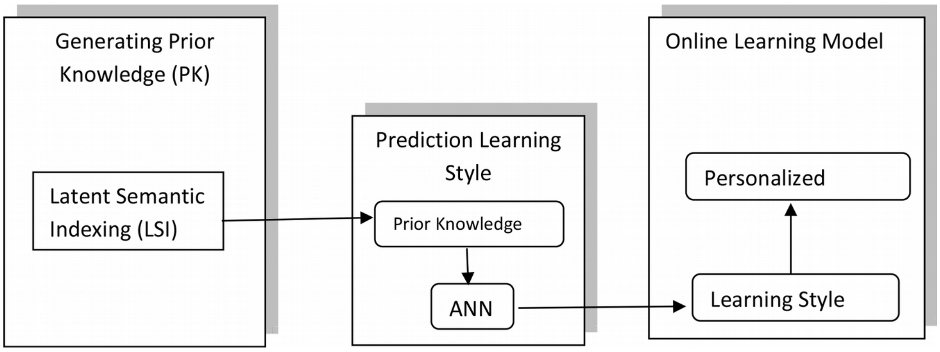

Figure 1. Methodology research

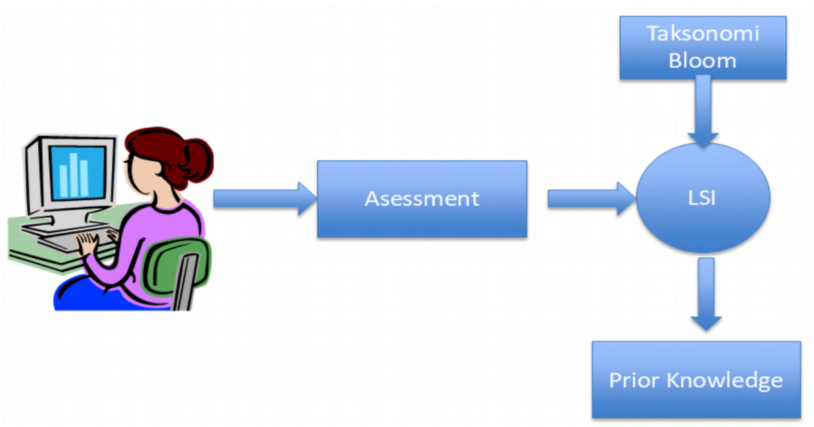

Figure 2. Prior knowledge architecture (Hasibuan & Nugroho, 2017)

In Figure 2 it can be seen that the learner will be given an assessment before starting the learning process. This assessment process is done to get the level of knowledge that has been owned by each learner. The level of prior knowledge or Prior Knowledge Level (PKL) can be divided into four levels: Knowledge of Fact (KOF), Knowledge of Meaning (KOM), Integration of Knowledge (IOK) and Application of Knowledge (AOK).

Knowledge of Fact is the knowledge that learners have with the lowest level. This level is characterized by the learner having only basic capacity such as being able to name, identify, name and encode. This learner only remembers something new usually with visualization. The second level, Knowledge of Meaning, is characterized by learners who already have the ability to explain, categorize, exemplify, explain, describe and present.

The Integration of Knowledge level is characterized by learners who have the ability to modify, produce, process, simulate and perform. Learners at this level already have skills and not just knowledge. The last level is the highest level, Application of Knowledge, which is characterized by the ability to break down, summarize, interpret, test and create. Figure 3 is a representation of prior knowledge.

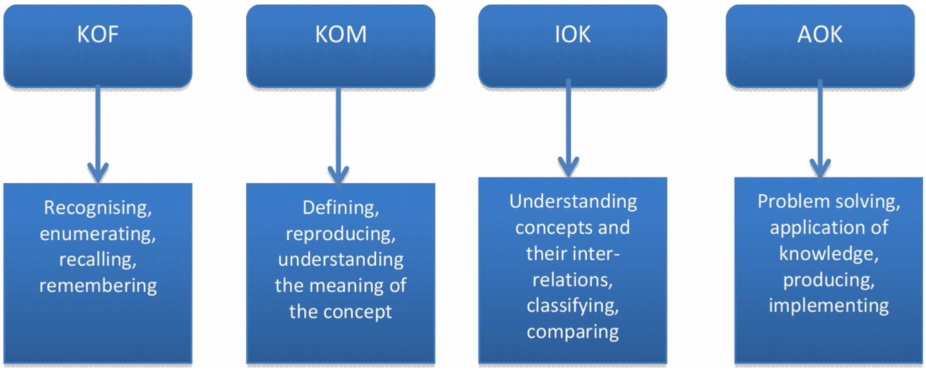

Figure 3. Representation of prior knowledge

The questions in this study are:

Mention and explain and provide examples of computer network topologies that exist today, and provide information on the strengths and weaknesses of each of the topologies and solutions for networking at XYZ Universities based on the information you have received.

This question has described 4 levels of Prior Knowledge, which can be detailed as follows:

1. KOF: specify computer network topology
2. KOM: explain the definition of computer network topology
3. IOK: Provide information on the advantages and disadvantages of each computer network topology
4. AOK: Give the right solution for computer network topology at XYZ College

The steps of LSI to process the answers are:

Step 1:

- Every answer from learners will be arranged into a matrix Prior Knowledge (PK). The value of matrix Matrix PK consists of answers from each learner divided into 4 levels, KOF, KOM, IOK and AOK.
- Build the answer keyword illustrated into Q

Step 2:

Decompose the PK matrix, where PK = USVT

Step 3:

Take the first 2 columns of U and V and the two rows and columns of S

Step 4:

Reduce 2 columns for V, this process is to find the eigenvector value which will be used in step 6. The value of v direduce becomes KOF, KOM, IOK and AOK

Step 5:

Find new queries with formulas: $q = q^T U_k S_k^{-1}$

Step 6:

Find the document ranking value with KOF, KOM, IOK and AOK values that will be used in the ANN method.

The second step is profiling learners by using ANN to predict VARK learning style. The profiling process is done by taking the assessment value obtained from the application of the Latent Semantic Indexing algorithm. The system architecture of LSI and ANN used for profiling learners can be seen in Figure 4.

In Figure 4 it can be seen that the assessment process is done at the beginning of the learning to generate prior knowledge of the learner. The method used to generate prior knowledge uses Latent Semantic Indexing (LSI). Assessment results are then used to predict learning style with ANN method.

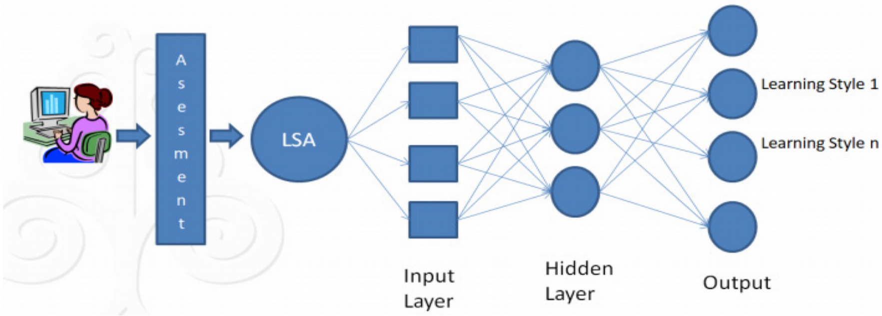

Figure 4. Architecture neural network for e-learning

4. Implementation Model

This research gathers prior knowledge on database subjects. Priority generation process uses LSI method. Some steps in using the LSI method can be seen in Figure 5.

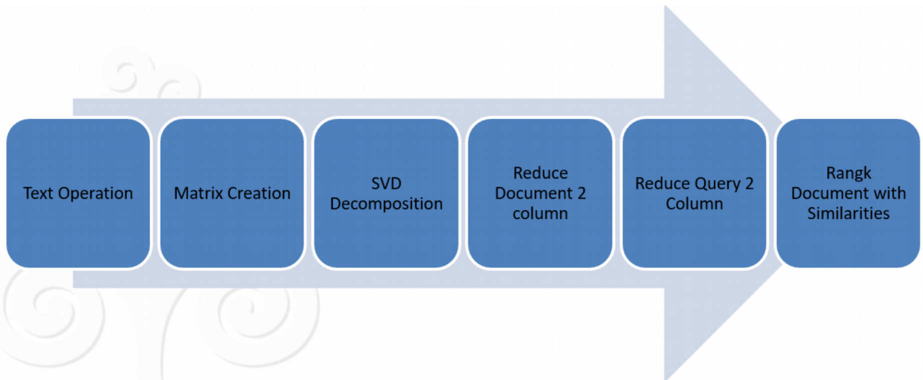

Figure 5. Step method LSI

The application of LSI method can be seen in Figure 5. The first step of the system is that each learner is given four questions. These four questions illustrate the level of prior knowledge of the learner. Any questions will be answered using the essay technique. The second step with the LSI method is to compose the answer from the sentence form into a form of words in the form of matrix A.

The next step after the LSI result is taken by converting the LSI value to the weight value to be used in the ANN method. The conversion can be seen in Table 2 below.

No	Prior Knowledge	Assessment Score	Weight
1.	Knowledge of Fact	0.8-0.9 0.6-0.7 0.4-0.5 0.2-0.3 -0.1-0.1	5 4 3 2 1
2.	Knowledge of Meaning	0.8-0.9 0.6-0.7 0.4-0.5 0.2-0.3 -0.1-0.1	5 4 3 2 1
3.	Integration of Knowledge	0.8-0.9 0.6-0.7 0.4-0.5 0.2-0.3 -0.1-0.1	5 4 3 2 1
4.	Application of Knowledge	0.8-0.9 0.6-0.7 0.4-0.5 0.2-0.3 -0.1-0.1	5 4 3 2 1

Table 2. Converts the value of prior knowledge

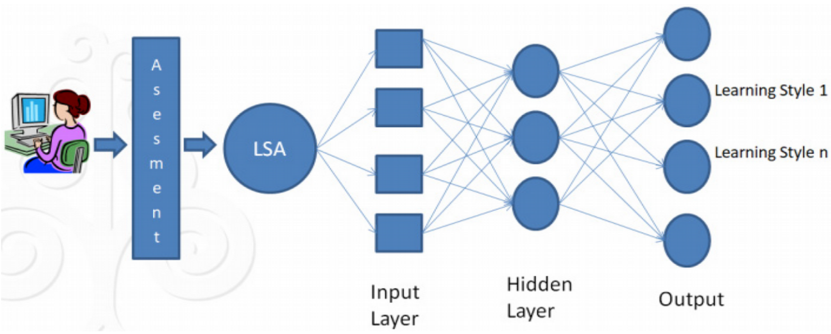

Figure 6. Artificial Neural Network For E-learning (ANNFE)

In Table 2 above it can be seen that there are four levels of prior knowledge. Each level of prior knowledge is grouped into five value ranges and five weighted values. The result of converting the value to prior knowlege (y1, y2, y3 ... yn) is what will be used on the artificial network to get the learning style learner profile prediction. The ANN architecture used can be seen in Figure 6.

In Figure above is the Architecture of Artificial Neural Network For E-learning which is a model used to get the profile of a learner. The result of the converted LSI value being the value of y1, y2, y3 ... yn being the input value.

The provisions of the use of artificial neural network:

Input = y1,y2,y3,y4

Bobot = w /weight

Number of all Input (pi) multiplied by weight (wi)

Output n = $\Sigma p_i.w_i$

Where Output / Output Neuron a = f(n)f = function

The division of learner levels into four parts as in Table 3 below are:

Id	Level Prior Knowledge
X1	Knowledge of Fact
X2	Knowledge of Meaning
X3	Integration of Knowledge
X4	Application of Knowledge

Table 3. Level prior knowledge

No	ID	Assessment LSI				Prior Knowledge				Prediction Learning Style	Prediction Learning Style Using ANN
		KOF	**KOM**	**IOK**	**AOK**	**X1**	**X2**	**X3**	**X4**		
1	2122	0.9	0.2	0.2	0.2	5	2	2	2	Visual	Visual
2	2123	0.8	0.8	0.8	0.5	5	5	5	3	**Read**	**Kinesthetic**
3	2124	0.9	0.5	0.5	0.3	5	5	3	2	Audio	Audio
4	2125	0.9	0.9	0.9	0.9	5	5	5	5	Kinesthetic	Kinesthetic
5	2126	0.4	0.5	0.1	0.1	3	3	1	1	Audio	Audio
6	2127	0.7	0.1	0.1	0.1	4	1	1	1	Visual	Visual
7	2128	0.8	0.1	0.1	0.1	5	1	1	1	Visual	Visual
8	2129	0.6	0.6	0.6	0.1	4	4	4	1	**Read**	**Audio**
9	2130	0.6	0.6	0.5	0.4	4	4	3	2	Audio	Audio
10	2131	0.6	0.6	0.6	0.6	4	4	4	4	Kinesthetic	Kinesthetic

Table 4. Result LSI and Prior Knowledge

accuracy: 80.00% +/- 40.00% (mikro: 80.00%)

	true Knowledge of ...	true Integration of ...	true Knowledge of ...	true Application of ...	class precision
pred. Knowledge o...	3	0	0	0	100.00%
pred. Integration of ...	0	0	0	0	0.00%
pred. Knowledge o...	0	1	3	0	75.00%
pred. Application of...	0	1	0	2	66.67%
class recall	100.00%	0.00%	100.00%	100.00%	

Table 5. Using ANN for Detection Learning Style

In Table 3 above one can see that input X1 is a representation of Knowledge of Fact. X2 is Knowledge of Meaning, X3 is a representation of Integration of Knowledge and X4 is Application of Knowledge.

Table 4 below is an assessment result using LSI and Prior Knowledge conversion results.

While table 5. Below is the result of using the ANN method to detect learning styles.

5. Conclusion

This research has succeeded in developing a model of learning style detection by using a prior knowledge approach. The prior knowledge generation process uses the Latent Semantic Indexing (LSI) approach. The LSI approach has succeeded in generating learners' learning styles more accurately than previous detection models. This successful because the detection process is carried out at the beginning of a new topic. Previous studies detected only the beginning of learning by using a vark questionnaire that did not relate to prior learning knowledge. After the process of generating learning styles with LSI is completed, the next step is to predict learning style by using ANN. To ensure that the vark learning style is appropriate, confirmation is made by giving online questions by adopting a vark learning style questionnaire. Further research is expected to develop a detection and prediction system that is integrated either with the Learning Management System or e-learning system.

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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