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Dynamics Personalized Learning Path Based on Triple Criteria using Deep Learning and Rule-Based Method

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***Abstract*—Personalized learning paths are designed to optimize learning time and improve student learning performance by providing an appropriate learning sequence based on the unique characteristics of each student. A common method for constructing personalized learning paths is based on the student's knowledge but disregards the student's interest in the subject matter. This research employs a deep learning and rule-based approach to recommend suitable material based on the topic's difficulty, student interest, and knowledge level. The difficulty level of the topic is predicted using deep learning. A questionnaire is used to determine the level of student interest, which is then processed using a rule-based approach to generate a learning path. Modeling a dynamic learning path requires measuring student knowledge in each topic and updating the learning path accordingly. Comparing the learning outcomes of students who utilized conventional e-learning versus those who followed a personalized learning path constitutes the evaluation. The results demonstrated that students scored 29% higher, or 15.06 points, than those who utilized conventional e-learning.**

Keywords— Personalized Learning Path, Rule-Based, Deep Learning, difficulty level, student interest.

I. INTRODUCTION

Personalization in the context of e-learning is a strategy to provide individual learning based on differences in learner characteristics. Many types of personalization can be offered to the students; one is a personalized learning path. A learning path is a route or learning sequence that students should go through to achieve learning outcomes. According to Bo Jiang [1], fixed learning sequences are unsuitable for all students because they have different abilities, interests, and learning styles.

With the application of artificial intelligence in education today, creating personalized learning paths (PLP) presents a number of challenges. Hui Li [2] compiled a PLP based on the student's ability level and the material's difficulty using the knowledge network approach. The research of Hui revealed that personalized learning paths could be designed more effectively than those created by experts, but it was not determined whether or not PLP improved student learning performance. In addition, Hui's research utilized only two parameters, excluding student interest, whereas according to Ten Hagen [3], learning interest also affects learning achievement. Interest in learning is a psychological characteristic of a student that includes enthusiasm, participation, and engagement in learning. The greater a student's interest in a subject, the greater their likelihood of researching it and learning it [4].

Based on the presentation of the research gaps, this study will examine PLP based on three criteria: the topic's difficulty level, the student's interest level, and the student's knowledge level. The challenge of this research is integrating these triple criteria to develop a system that can diagnose student interest, align it with the topic's difficulty level, and produce dynamic learning paths based on student knowledge level in each topic. The contribution of our research is to propose a deep learning and rule-based approach to create a dynamic personalized learning path and evaluate the impact of PLP on students compared with conventional E-learning.

The rest of the paper is organised as follows. Section II describes the related works in the literature. Section III describes the proposed method. Section IV discusses the results, main findings, and some limitations. Finally, Section V presents our conclusions.

II. RELATED WORK

Personalized learning paths are a method for designing students' learning sequences. The parameters used to compile the learning sequence are the characteristics and knowledge of the students, which are typically obtained through tests or questionnaires [5][6]. We used questionnaires to determine students' interests in this study.

Several parameters are widely used by researchers, such as learning style [7], learning objectives [8], and student preferences [9]. However, we have yet to find articles that use students' interests as parameters to build learning paths

Typically, researchers combine two or more characteristics; Vanitha et al. [10] and Nabizadeh et al. [11] use knowledge levels and learning objectives as parameters to design personalized learning paths. Simultaneously, Sarkar et al. [12] developed a learning pathway based on learning style and differentiated pedagogy. Learning paths are constructed by Nabizadeh et al. [11] and [13] using students' allocated time and knowledge levels. In this study, we used three parameters to create personalized learning paths with expectations that can improve students' learning outcomes, whereas all other studies use an average of two parameters. We cannot assert that the impact of using three parameters in building a learning path is greater than using two parameters because we cannot compare our research to other research. This is due to the fact that the dataset used in this study is a real dataset tested on Indonesian high school students. Other studies, on the other hand, rely on private datasets developed with diverse educational levels, origin countries, and learning cultures [10]. Therefore, we only measure the impact of this triple criterion on the learning outcomes of students [10] using pre- and post-test results in comparison to conventional e-learning. Several studies have utilized machine learning to develop learning paths. Chen et al. [9] proposed the establishment of a personalized learning path by diagnosing the proficiency of knowledge nodes based on the video-viewing behaviors of students using the LSTM technique. Wang et al. utilized student preferences and compared the most effective machine learning techniques in order to design personalized learning paths. According to Wang, CNN provided the highest score for precision [14]. We also implemented deep learning in the supporting system to generate learning paths based on this research.

III. Proposed Methods

In this study, several steps are needed to produce a personalized learning path as shown in Fig. 1. Briefly explained, CNN will be used to predict the difficulty level of learning material, Rule based will be used to create initial learning paths using student's interest and involvement level, while dynamic learning paths are generated using knowledge levels. The details of how to create personalized learning path according to figure 1 will be explained as follows:

A. Topic Difficulty Level Prediction using CNN

The topic's difficulty level has also been used in many previous studies as a parameter for constructing learning paths. One of them is Chen's research, which also makes use of expert labeling to determine the topic's level of difficulty [15]. Our research, which used CNN to predict the topic's difficulty level, also adopted Chen's research, and we collected a dataset of biology learning materials and labeled the difficulty level based on teacher expertise [16], as shown in Table I.

The purpose of predicting the topic's difficulty level is to ensure that learning material on the same topic from different sources has the same difficulty level. Determining the difficulty level is essential so that the material given to students is not too difficult or too easy according to their needs and abilities [15].

TABLE I. DIFFICYLTY LEVEL OF LEARNING MATERIAL

Topic	Sub Topic	Module	Difficulty Level
Cells as the Smallest Unit of Life and Bioprocesses in Cell	1. The Concept of Cells and the Chemical Components of Cells	1. Cell Concept	2
		2. Chemical Components of Cell Builders	2
	2. Structure and Function of Cell Parts	3. Prokaryotic and Eukaryotic Cell Structure	2
		4. Differences between Animal Cells and Plant Cells	1
		5. Membrane Transport Mechanism	2
	3. Bioprocesses in Cells	6. Protein Synthesis	3
		7. Cell Reproduction	2

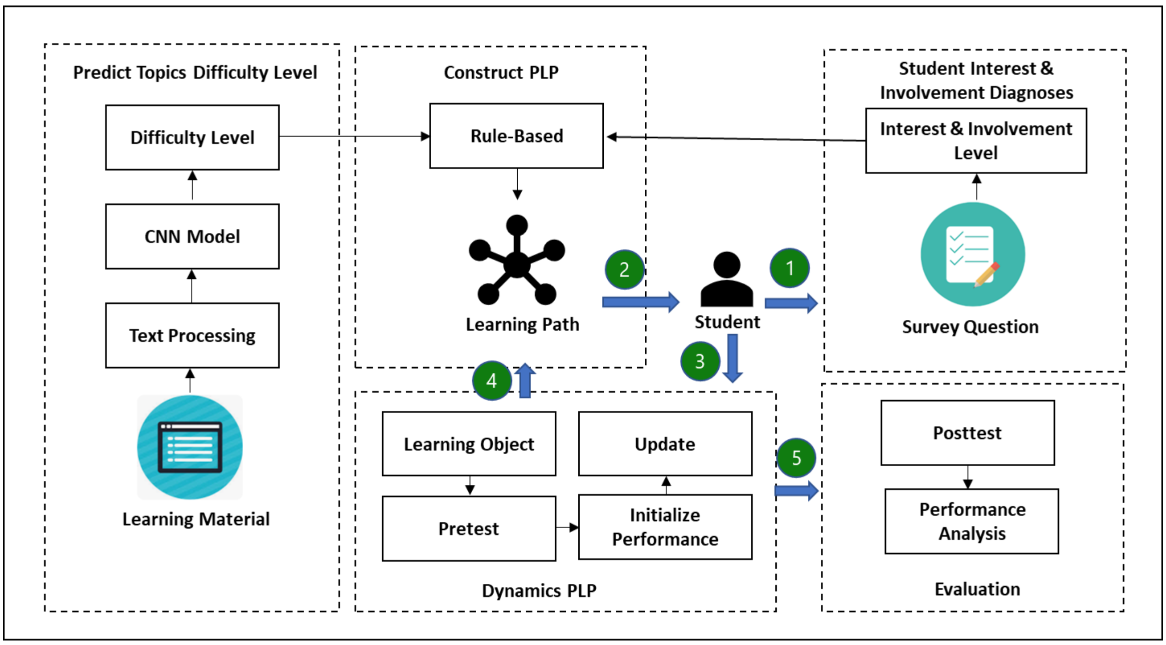

Fig. 1. The Proposed methods to construct Personalized Learning Path

B. Personalized Learning Path Construction Using Rule Based Method

A set of questions is given to students to determine their level of interest and involvement in a particular learning material. The questions that were asked to students are listed in Table II and referred to research conducted by Murni [17].

Rule-based is a method based on predetermined rules to produce output or decision according to some given inputs [18]. In this research, rule-based is used to create an initial learning path based on students' answers to the questions. A rule-based containing four rules, as shown in Fig. 2.

TABLE II. QUESTIONNAIRE OF STUDENT'S INTERESTS

Category	Question	Y	N
Interest	1. I was very interested in the material presented by the biology teacher.		
	2. I listened well during the Biology learning activity.		
	3. I want to take a biology practicum to be clearer.		
	4. I studied at home before attending biology lessons.		
	5. I aspire to become a professional biology teacher.		
Involvement	6. When I didn't understand the material explained, my teacher always asked.		
	7. I often look for information on the internet about biology lessons.		
	8. I will try hard in studying so that I can get high grades.		
	9. I prefer group study, because I can complete tasks together.		
	10. Group learning trains me to work together and be compact in learnin		

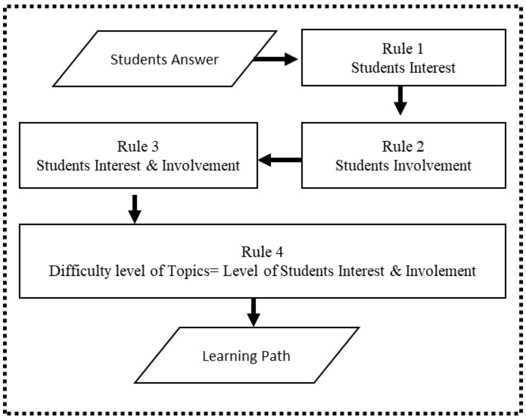

Fig. 2. Rule Based to Contruct Learning Path

- Rule 1

There are five questions with two select answer options provided for students, and it produces 32 rules, as shown in Table III. Rule 1 is designed to determine the rules for students' interest (SIN) levels. The SI level will be modeled as low (1), moderate (2), and high (3). The level will be high if the amount of "Y" or "yes" equals four or five in each question. The level is moderate if "Y" equals 2 or 3. Meanwhile, the level is low when "Y" equals 1 or 0. Below are some examples of using Rule 1 to identify SI levels in biology subjects.

IF (Q1='Y') and (Q2='Y') and (Q3='Y') and (Q4='Y') and (Q5='Y') THEN (SIN Level=3)
IF (Q1='Y') and (Q2='Y') and (Q3='Y') and (Q4='N') and (Q5='N') THEN (SIN Level=2)
IF (Q1='Y') and (Q2='N') and (Q3='N') and (Q4='N') and (Q5='N') THEN (SIN Level=1)

- Rule 2

Rule 2 determines the student's level of involvement (SIV) level, which is nearly identical to Rule 1. Additionally, there are five questions with two answer options, and 32 rules are generated. Some examples of using rules are as follows:

IF (Q6='Y') and (Q7='Y') and (Q8='Y') and (Q9='Y') and (Q10='Y') THEN (SIV Level=3)
IF (Q6='Y') and (Q7='Y') and (Q8='Y') and (Q9='N') and (Q10='N') THEN (SIV Level=2)
IF (Q6='Y') and (Q7='N') and (Q8='N') and (Q9='N') and (Q10='N') THEN (SIV Level=1)

TABLE III. RULE TO PREDICT STUDENTS INTEREST

Rule	Q1	Q2	Q3	Q4	Q5	Level
1	Y	Y	Y	Y	Y	3
2	Y	Y	Y	Y	N	3
3	Y	Y	Y	N	Y	3
4	Y	Y	Y	N	N	2
5	Y	Y	N	Y	Y	3
6	Y	Y	N	Y	N	2
7	Y	Y	N	N	Y	2
8	Y	Y	N	N	N	2
9	Y	N	Y	Y	Y	3
10	Y	N	Y	Y	N	2
11	Y	N	Y	N	Y	2
12	Y	N	Y	N	N	2
13	Y	N	N	Y	Y	2
14	Y	N	N	Y	N	2
15	Y	N	N	N	Y	2
16	Y	N	N	N	N	1
17	N	Y	Y	Y	Y	3
18	N	Y	Y	Y	N	2
19	N	Y	Y	N	Y	2
20	N	Y	Y	N	N	2
21	N	Y	N	Y	Y	2
22	N	Y	N	Y	N	2
23	N	Y	N	N	Y	2
24	N	Y	N	N	N	1
25	N	Y	Y	Y	Y	3
26	N	N	Y	Y	N	2
27	N	N	Y	N	Y	2
28	N	N	Y	N	N	1
29	N	N	N	Y	Y	2
30	N	N	N	Y	N	1
31	N	N	N	N	Y	1
32	N	N	N	N	N	1

- Rule 3

Rule 3 is employed to combine Rules 1 and 2. We represent both the student interest and the student involvement (SINV) measures. Rule 3 contains a total of nine rules. Below are all the rules that can be generated. The higher the level of a rule, the stronger the relationship between students' interest level and their involvement.

IF (SIN=1) and (SIV=1) THEN (SINV Level=1)
IF (SIN =3) and (SIV=3) THEN (SINV Level=3)
IF (SIN =1) and (SIV=2) THEN (SINV Level=2)
IF (SIN=1) and (SIV=3) THEN (SINV Level=2)
IF (SIN=2) and (SIV=1) THEN (SINV Level=2)
IF (SIN=2) and (SIV=2) THEN (SINV Level=2)
IF (SIN=2) and (SIV=3) THEN (SINV Level=3)
IF (SIN=3) and (SIV=1) THEN (SINV Level=2)

IF (SIN=3) and (SIV=2) THEN (SINV Level=3)

- Rule 4

  Rule 4 is the final rule, which is intended to obtain a set of modules required to structure the initial learning path. The left-hand side of this rule corresponds directly to the level of SINV produced in Rule 3. The right-hand side of the rule contains a set of difficulty levels (SDL), each of which corresponds to all modules having a difficulty level equal to or greater than the value of the SINV level of the preceding part of the rule. This rule contains three rules, as shown below.

IF (SINV Level=3) THEN (SDL = {3})
IF (SINV Level=2) THEN (SDL = {2, 3})
IF (SINV Level=1) THEN (SDL = {1, 2, 3})

The following example illustrates how the rule-based method shown in Figure 2 is applied to generate an initial learning path. Suppose that Student A gives the following answers to all questions listed in Table II: SIN = [Y, Y, N, Y, N], and SIV = [N, N, Y, N, Y]. Applying Rule 1 to SIN will produce a SIN level of 2. Similarly, applying Rule 2 to SIV will produce SIV level = 2. Next, applying the combination of values of these SIN and SIV levels to Rule 3 will produce SINV level = 2. Applying this resulting SINV level to Rule 4 will produce SDL = {2, 3}. The result of Rule 4 indicates that all modules having difficulty levels equal to 2 and 3 must be generated as an initial learning path for Student A, i.e., M1(2), M2(2), M3(2), M5(2), M7(2), and M6(3). In this learning path, the number within a bracket shows the difficulty level of a module. The list of the modules of the learning path is constructed in ascending order of the modules having the same difficulty value.

C. Dynamic Personalized Learning Path

According to Outmane's research [19], student characteristics and preferences are dynamic, so the learning path must also be dynamic. The rule-based learning path construction explained in the previous section only produces a static learning path, but it can be made dynamic according to the student's knowledge level. We used the knowledge level of the students since each student may have different knowledge of a particular module. We use a post-test for every module of a topic to determine students understanding of each module. If the score of the post-test is less than 75, then the student has two choices: go down to the module with a lower difficulty level or repeat the module.

Fig. 3 shows an example of how the dynamic learning path construction works for a student A with a given initial learning path explained earlier, i.e., M1(2), M2(2), M3(2), M5(2), M7(2), and M6(3). Before the student can continue to undertake module M2, he must perform a post-test. If the score of his post-test exceeds 75, he will be able to continue to undertake module M2. However, if the score is below 75, he will be privy to a decision to choose whether to repeat module M1 or go down to undertake the module having a lower difficulty level than that of module M1, i.e., module M4 (see Table I). If he decides to choose module M4, the new learning path (i.e., M4(1), M1(2), M2(2), M3(2), M5(2), M7(2), and M6(3)) must be followed.

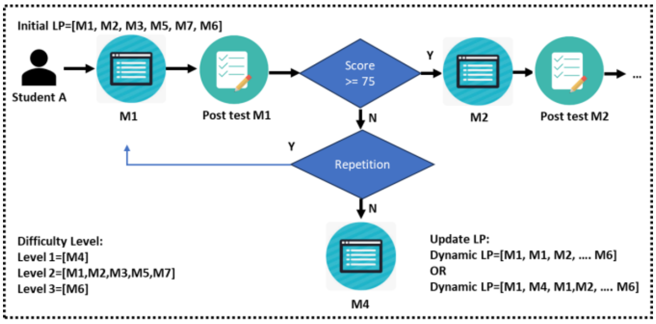

Fig. 3. Knowledge Level Identification Process to Construct Dynamic Learning Path

D. Evaluation

Evaluation of the proposed method is obtained by dividing one class into two groups; Group A is a group that uses traditional E-learning without personalization. Group B is a group that uses PLP E-learning (E-PLP). We will compare the average results of students in Group A and B to find out whether PLP can improve student learning performance or not[6][20].

IV. RESULTS AND DISCUSSION

The experiment was conducted with 36 students in Class XI of a Senior High school located in Kalianget, Sumenep, Indonesia. The whole class is divided into two groups, each of which consists of 18 students. The evaluation is done by comparing pretest and posttest scores [21]. However, to make this study more objective, we also compared each group's pretest and posttest scores before and after using our proposed method.

A. Pretest Results Analysis

This analysis measures the abilities of each group before using the system. By knowing students' abilities before using the system, we hope it will be more objective to see the effect of using E-PLP on student achievement. In Fig. 4, we compare the pretest scores between Groups A and B. The pretest results showed that Groups A and B have varying pretest scores, with the number of students getting almost equal scores as shown in Table IV and Fig. 4.

TABLE IV. RANGE OF PRETEST SCORE

Group	Score		Total Students
	0-50	51-100	
A	7	11	18
B	6	12	18

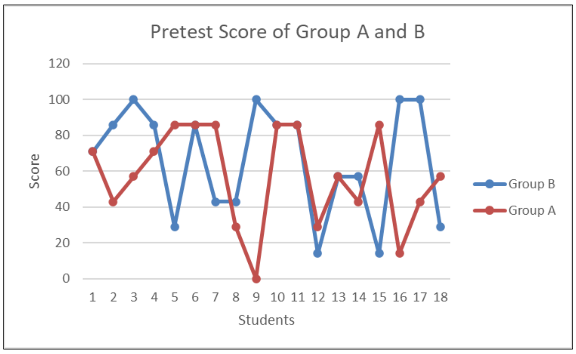

Fig. 4. Comparison pretest of Groups A (E-learning) and B (E-PLP)

B. Posttest Results Analysis

This analysis compares learning outcomes in both groups using E-learning and E-PLP based on posttests. A posttest is given to students who have completed the material suggestions in the system a dynamic learning path for E-PLP and a default learning path in E-learning.

TABLE V. RANGE OF POSTTEST SCORES

Group	Score		Total Students
	0-50	51-100	
A	10	8	18
B	3	15	18

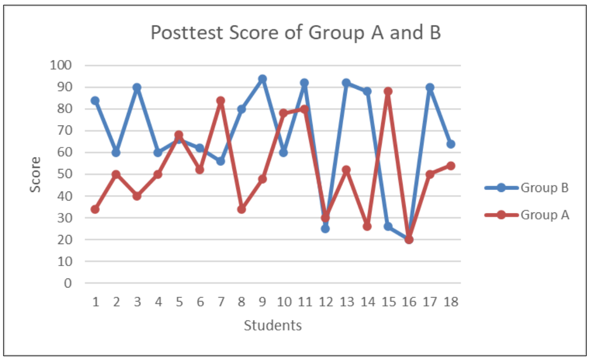

Fig. 5. Comparison posttest of Groups A (E-learning) and B (E-PLP)

Comparison Posttest of E-learning and E-PLP According to the data presented in Table V, it is evident that within Group A, a total of ten students achieved scores below 50, while eight students attained scores exceeding 50. The population of students in Group B who achieved scores exceeding 50 witnessed an increment, reaching 15 students. Conversely, the number of students who obtained scores below 50 amounted to merely three.

The findings are presented in Figure 5 and Table V, indicating that Group B exhibits a superior level of achievement compared to Group A. As indicated in Table VI, it can be observed that Group B achieved a mean value of 15.06, which is greater than that of Group A. The standard deviation value of Group B was found to be 3.76, which was observed to be greater than that of Group A.

TABLE VI. DESCRIPTIVE ANALYSIS OF POSTEST OF E-LEARNING AND E-PLP

Descriptive	Group A	Group B
Population	18	18
Mean	52.11	67.17
Median	50.00	65.00
Standard Deviation	20.36	24.12
Standard Error	4.80	5.69

C. Pretest and Posttest Results Analysis

The previous analysis found that Group B had higher learning outcomes than Group A. This was shown from the posttest results. We also made a comparison by analyzing the pretest and posttest values of the two groups.

Table VII shows that the mean value of Group A decreased to 5.11, but that of Group B increased by 1.23. The standard deviation of Group A decreased to 6.96 points, but the standard deviation of Group B only decreased by 6.57. The visualization results of Group pretest and posttest scores can be seen in Fig. 6.

TABLE VII. DESCRIPTIVE ANALYSIS OF PRETEST AND POST TEST OF E-LEARNING AND E-PLP

Descriptive	Gorup A		Group B	
	Pretest	Posttest	Pretest	Posttest
Population	18	18	18	18
Mean	57.22	52.11	65.94	67.17
Median	57.00	50.00	78.50	65.00
Standard Deviation	27.32	20.36	30.69	24.12
Standard Error	6.44	4.80	7.23	5.69

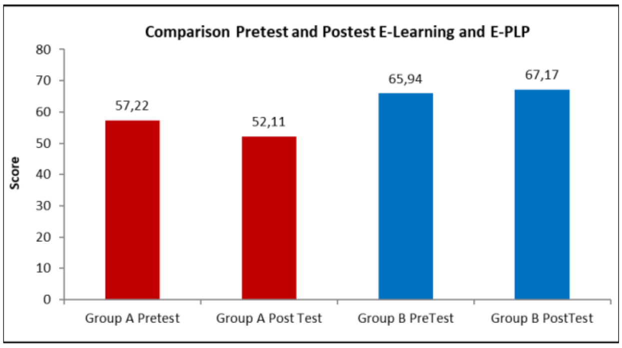

Fig. 6. Comparison Pretest and Postest of E-learning and E-PLP

V. CONCLUSION

In this study, we concluded that personalized learning paths can increase student achievement better than E-learning. This is shown by an increase in the posttest score in E-PLP and a decrease in the score in E-learning. Based on the analysis, it is known that personalization of learning paths makes students more challenged because there is a dynamic PLP that assists in detecting their level of understanding and provides a choice of whether to repeat the topic or go down to a topic with a lower difficulty level. It provides more opportunities for students to determine their weaknesses early.

In future studies, we recommend cross-over testing for better testing methods, where students who initially use e-learning are replaced with E-PLP, and vice versa. With this cross-over testing, the research results are expected to be more objective

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