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Comparing Student Model Accuracy with Bayesian Network and Fuzzy Logic in Predicting Student Knowledge Level

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Abstract

The use of computer has widely used as a tool to help student in learning, one of the computer application to help student in learning is in the form of Intelligent Tutoring System. Intelligent Tutoring System used to diagnose student knowledge state and provide adaptive assistance to student. However, diagnosing student knowledge level is a difficult task due to rife with uncertainty. Student Model is the key component in Intelligent Tutoring System to deal with uncertainty. Bayesian Network and Fuzzy Logic is the most widely used to develop student model. In this paper we will compare the accuracy of student model developed with Bayesian Network and Fuzzy Logic in predicting student knowledge level.

Keywords: *Student Model; Intelligent Tutoring System; Fuzzy Logic; Bayesian Network*

1. Introduction

Computer application has widely used to help student in learning. Intelligent Tutoring System is one of the computer applications that used to help student in learning. Intelligent Tutoring System is an interactive learning environment supported with computer program to adapting with the student. Intelligent used to diagnose student knowledge level. In diagnosing student knowledge level there are three step of process. First is acquire information about the student, second is process the information to analyze and update the student model, third use the student model adapting to the student. However, diagnosing student knowledge level is a difficult task due to rife with uncertainty. Student Model is core component in Intelligent Tutoring System used to deal with uncertainty, especially when the student is not meet face to face to the teacher [1]. Student model contain individual characteristics and cognitive groups into knowledge component. Knowledge component contain information correlate to student knowledge level, student personal preference in learning and psychological characteristics [12]. Research found that Bayesian Network and Fuzzy Logic is the most widely used to develop student model [3]. Bayesian Network is tools to manage knowledge from different situation in one connected unit [4]. Fuzzy logic is able to increase Intelligent Tutoring System performance in decide what feedback and material that must give to the student. Fuzzy logic also able to increase the ability of a system to make the right decision [3].

The comparison between Fuzzy Logic and Bayesian Network in the outside student model field has been done in the previous research. For example, the comparison between Fuzzy Logic and Bayesian Network in predicting crop yields and economic returns [16]. After that, there is a research comparing Fuzzy Logic and Bayesian Network in predict the futuristic export information of fresh mango quantity [17]. Furthermore, there is also research

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comparing Fuzzy Logic and Bayesian Network in modeling pump system [18] and modeling habitat suitability [19].

2. Literature Review

Student model

Student modeling is a process to gain the information about the student and transform the information into the student representation called student model [7]. Student Model is one of the Intelligent Tutoring System that contains information about the student such as knowledge level [5]. In Intelligent Tutoring System, student model used to deals with uncertainty when diagnosing student knowledge level.

According to domain subject student model consist of two part :

- Domain specific information (DSI) which represent student knowledge level in a domain subject.
- Domain independent information (DII) which consist learning goal, cognitive aptitude, historical data and motivation state measurement [12].

Student model has widely used for making inference about student attribute. It process is to observe student performance like the degree of correct a student in answer a set of problem. Beside observe student performance it is also observe on a student action. Student model use the observed information to predict student attribute such as foal, preference, knowledge and motivational state, where those attributes are unable to determined directly.

In Intelligent Tutoring System student modeling has two primary tasks. The first task is to predict student behaviors, such as predict student knowledge level in the next concept in learning. The second task is to acquire acceptable parameter estimates, where acceptable means how accurate the parameter which usually measure by compare to a standard [13].

Bayesian network

Bayesian Network is tools to manage knowledge from different situation into one connected unit. Bayesian Network structure called directed acyclic graph (DAG). In DAG there two important components, first is variable which is represented as node and the second is edge which is representing relationship between variables.

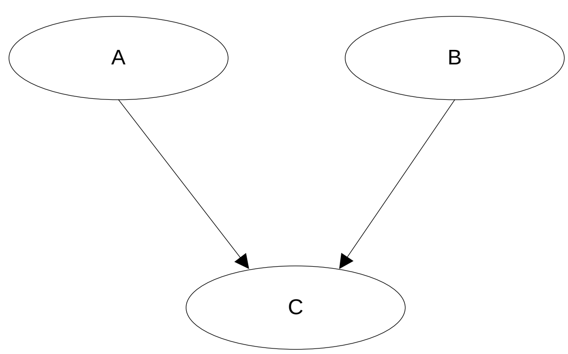

Figure 1. DAG Bayesian Network

Every node in Bayesian Network has probability value and the value always change each time receiving evidence. The probability value before receive any evidence called *prior probability*. After receive an evidence probability value will updated, the new probability value called *posterior probability*. *Full joint probability distribution* form all variable in Bayesian Network acquire from conditional probability each variable based on all variable's parent. Inference procedure needs prior probability from root node and conditional probability from root beside root node.

For example in Figure 1. DAG has three nodes A, B and C. Node A has an arrow point to node C this means that A is parent node of C. Based on marginalization in Bayesian Network [8], the probability in node C can count as

$$P(C) = \sum_{A,B} P(A,B,C) = \sum_{A,B} P(C \mid A,B) P(A) P(B) \qquad (1)$$

If node A receive an evidence, an inference process will occur then node C will updated as

$$P(C \mid A) = \sum_{B} P(C \mid A,B) P(B) \qquad (2)$$

P (B) is the probability of node B and *P(C | A B)* is the probability of node C when A and B value are true, this probability get from the Conditional Probability.

Bayesian Network has three advantages, first is consistent and complete representation that guaranteed to define probability distribution to all variable in the network. After that, Bayesian Network consistency and completeness guaranteed by localization test that variable only affected by variable that direct connected. Finally, Bayesian Network able to defines probability distribution exponentially using probability polynomial number.

Fuzzy logic

Fuzzy Logic technique used to deals with uncertainty in real world problem caused by inaccurate data like human subjectivity. In system modeling also often involved variables with uncertain value, this uncertain value resolved using fuzzy set theory. Fuzzy set described by variable that have value like *"low"*, *"normal"* and *"high"* rather than boolean value such as *"true/false"* or *"yes/no"* [6]. Fuzzy set determine by membership function expressed with $\mu_A(x)$

$$\mu_A(x): X \to [0,1], where\ \mu_A(x) = \begin{cases} 1, & x\ absolutely\ in\ A \\ 0, & x\ absolutely\ not\ in\ A \\ (0,1), & x\ partially\ in\ A \end{cases}$$

Value of $\mu_A(x)$ called *membership degree* and has value between 0 and 1 [5]. When x considered owned by set A , $\mu_A(x)$ value is 1 and when $\mu_A(x)$ is not considered owned by set A $\mu_A(x)$ is 0. The higher the membership function value, x will have stronger degree to be owned by set A.

Bayesian network in student modeling

There many student models developed with Bayesian Network, for example ANDES. ANDES is an Intelligent Tutoring System for learning physics [10]. Beside ANDES, there is also BITS an Intelligent Tutoring System for learning Computer Programming [1]. In BITS each concept represent as a node in the Bayesian Network. The student model in BITS represent student knowledge for each concept and predict the knowledge level of the next concept that never been learned by the student. So, BITS can tell the student which concept is already to learn and which concept still not ready to learn.

There is also research develop Intelligent Tutoring System for Learning Object Oriented [9]. In this research the conditional probability distribution was count using *slip* & *guess* value with equation

$$P(ku = true|p_1(ku)_i = true) * \ldots * P\big(ku = true\big|p_1(ku)_j = false\big) = (1 - slip) * \ldots * guess = \prod_{i \in K}(1 - slip) \prod_{j \in \overline{K}} guess . \quad (3)$$

Slip is the probability student fail to learn a concept when he knows one of the prerequisite concepts. *Guess* is the probability student success to learn a concept when he does not know any prerequisite concepts. The research shows that the student model able to produce accurate diagnostic student knowledge when the *slip* and *guess* value are equal and set in small value.

Fuzzy logic in student modeling

Fuzzy Logic also often to use in developing student model in an Intelligent Tutoring System, for example is student model that used in Intelligent Tutoring System for Learning Pascal [2]. In this research, the domain concept is represent as hierarchical tree, each concept represent as a node and each concept which is followed by other concept is connected by an edge. The fuzzy set used for describing student knowledge in a domain and the fuzzy rule is applied to inferring student knowledge level in concept connected by an edge. The student model in the Intelligent Tutoring System used to predict student knowledge level in a concept. In addition, Fuzzy Logic has been used to represent student model in Intelligent Tutoring System for learning geometry [14] and learning Software Design Pattern [11]. The student model used to predict percentage of error a student makes in finishing the next problem. Furthermore, Adaptive Learning System to help the student memory the content and improve their comprehension has been developed. The adaptive learning system develop based on fuzzy set theory able to estimate the learner knowledge level using test correspond to the learner target [15].

3. Research Method

In this section we will describe our research method. In this research we will develop two applications, the first application will include student model developed with Fuzzy Logic and the second application include student model developed with Bayesian Network. Our student model is used for modeling student knowledge in learning C Programming Language. Six concept based on [2] will include in the student model are shown as the table below

Table 1. Domain concept

Concept	*Description*
C1	*Sum in For Loop*
C2	*Calculation AVG in For Loop*
C3	*Counting in For Loop*
C4	*Sum in While Loop*
C5	*Counting in While Loop*
C6	*Calculation AVG in While Loop*

Fuzzy logic student model

First we will describe Fuzzy set and Membership Function that based on [2]. The Four fuzzy set will defined to describing student knowledge are

- Unknown (Un) : if the degree of success in domain concept between 0% - 60%.
- Unsatisfactory Known (UK) : if the degree of success in domain concept between 55% - 75%.
- Known (K) : if the degree of success in domain concept between 70% - 90%.
- Learned (L) : if the degree of success in domain concept between 85% - 100%.

The Membership Function for the fuzzy set is describe as follow.

$$\mu_{\mathrm{Un(x)}} = \begin{cases} 1, & x \leq 55 \\ 1 - \dfrac{x-55}{5}, & 55 < x < 60 \\ 0, & x \geq 60 \end{cases}$$

$$\mu_{\mathrm{UK(x)}} = \begin{cases} \dfrac{x-55}{5}, & 55 < x < 60 \\ 1, & 60 \leq x \leq 70 \\ 1 - \dfrac{x-70}{5}, & 70 < x < 75 \\ 0, & x \leq 55 \text{ } or \text{ } x \geq 75 \end{cases}$$

$$\mu_{\mathrm{K(x)}} = \begin{cases} \dfrac{x-70}{5}, & 70 < x < 75 \\ 1, & 75 \leq x \leq 85 \\ 1 - \dfrac{x-85}{5}, & 85 < x \leq 90 \\ 0, & x \leq 70 \text{ } or \text{ } x \geq 90 \end{cases}$$

$$\mu_{\mathrm{L(x)}} = \begin{cases} \dfrac{x-85}{5}, & 85 < x < 90 \\ 1, & 90 \leq x \leq 100 \\ 0, & x \leq 85 \end{cases}$$

x in membership function is student degree of success in a concept.

Next, we will define the membership function dependency and fuzzy rule that will use for inference process. In this research we will use membership function dependency and fuzzy rule that have been describe in [2]. Membership function dependency use to define the relationship between the concepts as shown in Figure 2. and define how strong is the relationship between the concepts as shown in Table 2. In learning programming when a student success to learn a concept, he will also have some knowledge about the following concept. For example, when a student have learn “Calculation average in For loop” and

"Counting in While loop" concept, he might also have some knowledge about "Calculation average in While loop" concept, which is the following concept of "Calculation average in For loop" and "Counting in While loop".

The relationship between *Ci* concept and *Cj* will denoted by *Ci* → *Cj*, where *Ci* is concept that precedes *Cj*, Based on that relationship there will two fact that possible to happen. First is based on the *Ci* result, the knowledge level in *Cj* will increase. The second is based on the *Ci* result, the knowledge level in *Cj* will decrease. Each time student finish test in a concept the knowledge level of all related concept will updated. In updating the knowledge level for the related concept we will use the membership function dependency value in Table 2. In Table 2 membership function $\mu D(Ci, Cj)$ describe the relation to update *Cj* based on *Ci* result.

Table 2. Membership Function Depedency

Ci	*Cj*	$\mu D(Ci, Cj)$
C1	*C4*	*1*
C1	*C2*	*0.81*
C2	*C6*	*0.52*
C1	*C3*	*0.45*
C3	*C5*	*1*
C4	*C5*	*0.45*
C4	*C6*	*0.39*
C5	*C6*	*0.41*

Based on the *Ci* → *Cj* relationship we will update *Cj* knowledge level using the following Fuzzy Rule. According to *Ci* knowledge level, *Cj* knowledge level will increase, where S1 is a higher knowledge level than S2.

- Rule 1 : If *Ci* and *Cj* knowledge level is S1 then *Cj* knowledge level keep S1 with $\mu S1(Cj) = max[\mu S1(Cj), \mu S1(Ci) * \mu D(Ci, Cj)]$.
- Rule 2 : If *Ci* is S1 and *Cj* is S2 then *Cj* will become S2 with $\mu S2(Cj) = \mu S2(Cj) * \mu D(Ci, Cj)$.

According to *Ci* knowledge level, *Cj* knowledge level decrease using the following rule :

- Rule 3 : If *Cj* is 100% Learned then *Cj* value will not updated.
- Rule 4 : If *Cj* is S and *Ci* is Unknown then *Cj* will become Unknown with $\mu Un(Cj) = \mu Un(Ci) * \mu D(Ci, Cj)$.
- Rule 5 : If *Cj* is S and *Ci* is Unsatisfactory Known then *Cj* will become Unsatisfactory Known if $\mu D(Ci, Cj) = 1$ or become Known with $\mu K(Cj) = 1 - \mu Uk(Cj) = 1 - \mu Uk(Ci) * \mu D(Ci, Cj)$. S is knowledge level state higher than Unsatisfactory Known.

- Rule 6 : If *Cj* is Learned with degree < 100% and *Ci* is Known then *Cj* will keep Known with $\mu K(Cj) = \mu K(Ci) * \mu D\ (Ci\ , Cj)$.

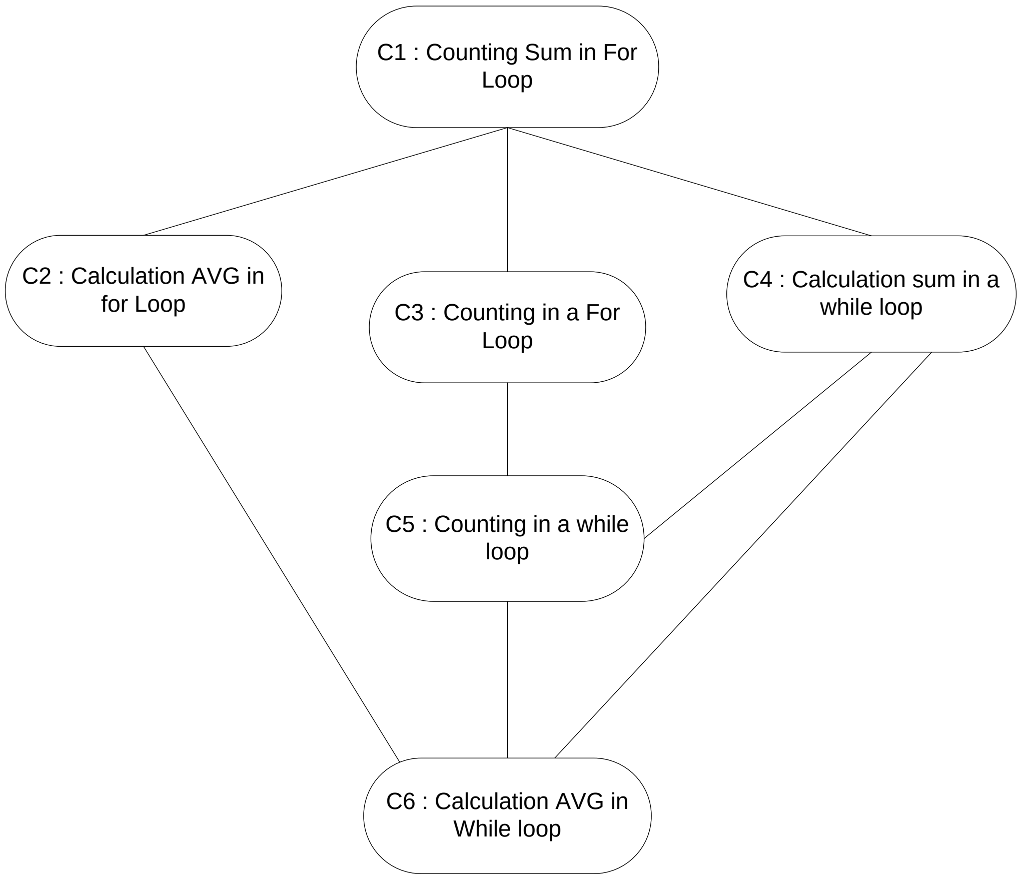

Figure 2. Domain Concept Relationship

Bayesian network student model

In Bayesian Network each domain concept presented as a node. First we will develop DAG to represent the relation between domain concept nodes in Bayesian Network. Based on the domain concept in Table 1. our DAG is shown in Figure 3. In the DAG, if a concept has a relation to other concept there will be an arrow connected both concept. For example, in Figure 2. *"Counting in a For Loop"* , *"Calculation Sum in a While Loop"* and *"Counting in a While Loop"* nodes are connected. In this case *"Counting in a For Loop"* and *"Calculation Sum in a While Loop"* are predecessor concept for *"Counting in a While Loop"* concept. So, if the student has success in learning *"Counting in a For Loop"* and *"Calculation Sum in a While Loop"* he might already have knowledge about *"Counting in a While Loop"* concept.

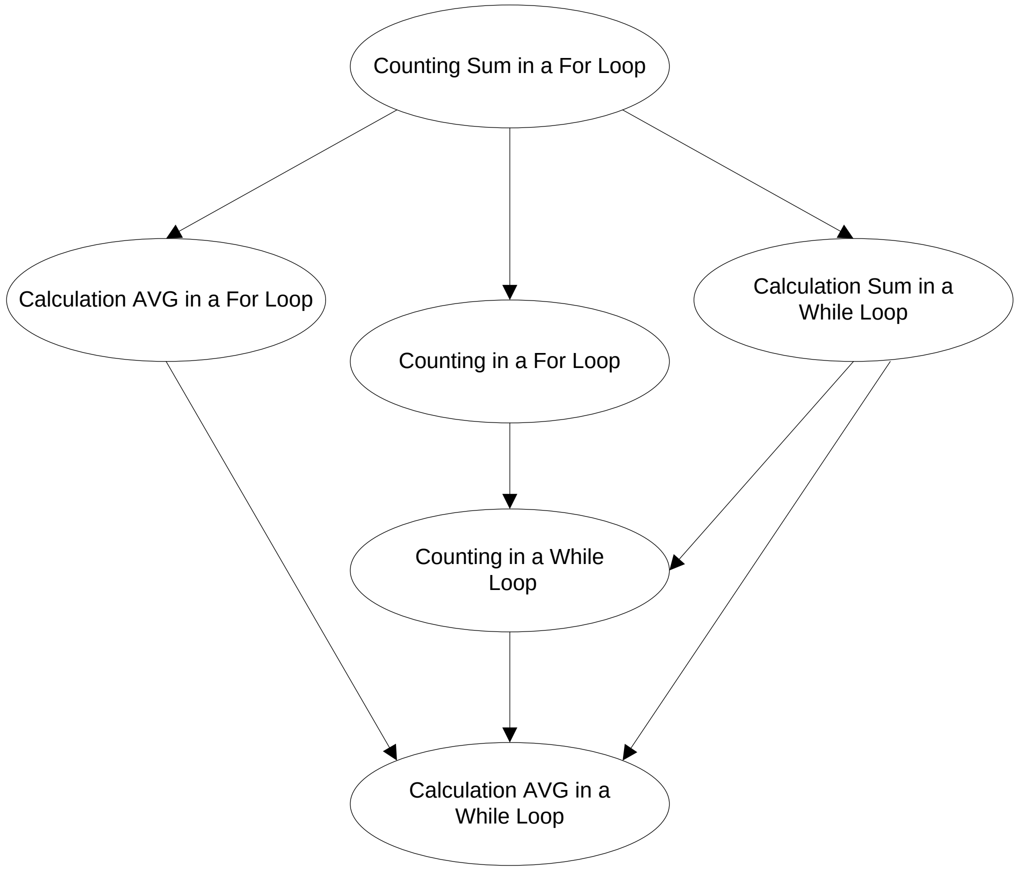

Figure 3. DAG domain concept

To find out the probability student has learned the next concept we have to define the conditional probability conditional probability distribution for each concept. The conditional probability distribution will calculate using equation (1) with the slip and guess value is 0.1 [9]. The example of conditional probability table for "*Counting in While Loop*" is shown in Table 3. After the conditional probability distribution defined we can get the posterior probability. Posterior probability is the new probability value after received an evidence. Each time a concept receives evidence, posterior probability calculation will done to all nodes related to the concept. The posterior probability calculation will done using formula (1).

Table 3. Conditional Probability Counting in a While Loop

Counting in a For Loop	*Sum in a While Loop*	*p(Counting in a While Loop| Counting in a For Loop, Sum in a While Loop)*
known	*known*	*0.81*
known	*not known*	*0.09*
not known	*known*	*0.09*
not known	*not known*	*0.01*

Every node in Bayesian Network will have Boolean value *known* or *not known*. A concept will receive evidence *known* when the success answer > 70% the problem in domain concept and will receive *not known* when success answer < 55%. The number is based on the fuzzy set that have described previously. A concept considered as *learned* when the probability *p(concept = known|evidence)* >= 0.70 [1].

Application Structure

In this research we develop two applications that will use in evaluation. The first application consist student model developed with Fuzzy Logic and the second application consist student model developed with Bayesian Network. The applications develop using C# programming language. Below are modules used in the applications.

- Main Module

  This module is used in both application and have classes as follow :

  - Case Form : this class provide user interface to show the cases that must be done by the student.
  - Case Control : this class will generate case from database to show in the case form.
  - Domain Concept : class represent every domain concept.

- Fuzzy Logic Module

  This module only used in application develop with Fuzzy Logic as student model and will have classes as follow :

  - Fuzzy Depedencies :class represent the relationship between concept.
  - Fuzzy Inference : this class implement the fuzzy rule to predict student knowledge level.

- Bayesian Network Module

  This module only used in application consist student model developed with Bayesian Network and will have classes as follow :

  - BNInference : this class doing the inference process and update probability to each domain.

4. Evaluation

The participants of the evaluation are Undergraduate Student in Bina Nusantara University, the student are the 3rd Semester in Computer Science Major. The student will split into two groups, each group consists of 24 student. Group 1 will do the test using application which develop with Fuzzy Logic for student model and group 2 use the application developed with Bayesian Network for the student model. In the test, students have to answer all the case in the six concepts. Each time the student finish answer all case in a concept, based on the degree of correct of the student answer the student model will predict the next concept whether considered as *learned* or not.

In order to measure the student accuracy we will define two variables. First is *prediction_time* to count how many times the student model predicts a student able to success in a concept. The value of *prediction_time* is increase by 1 every time student model considered the concept that has not been test by the student as *learned*. The second variable is *correct_prediction* to represent when the student is success in a domain concept when the student model has already predicts that domain as *learned*. The *correct_prediction* value will increase by 1 every time the student able to answer correctly 85% in a domain that has been considered as *learned* by the student model. The accuracy of student model will count as follow.

$$accuracy = \frac{average\ of\ correct\_prediction}{average\ of\ prediction\_time} \times 100\% \qquad (4)$$

After that we will compare the average accuracy of student in first and second. From the test we get the accuracy result for both groups as follow

Table 4. Group 1 result

Group1 – Fuzzy Logic	
Average of prediction_time	*3.33*
Average of correct_prediction	*2.87*
Accuracy	*86.25%*

Table 5. Group 2 result

Group2 – Bayesian Network	
Average of prediction_time	*2.91*
Average of correct_prediction	*2.62*
Accuracy	*90.00%*

The student model accuracy graphic comparison between Fuzzy Logic and Bayesian Network shown in Figure 4.

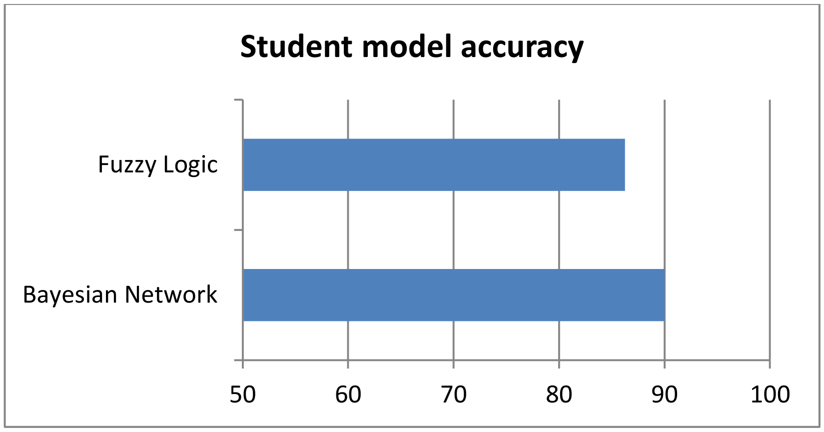

Figure 4. Comparison Student Model Accuracy

5. Conclusion

From the result of the evaluation we get the accuracy student model with Fuzzy Logic is 86.25 % and student with Bayesian Network in student model is 90.00%. So, we conclude that Bayesian Network have higher accuracy than Fuzzy Logic in predicting student knowledge level. For the next research we plan to use fuzzy set and membership function in Bayesian Network to determine when evidence will give to a domain concept. There is also a research to determine an accurate value membership value dependency.

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