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Bayesian-ANFIS Student Model for an Intelligent Tutoring System

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ABSTRACT
Intelligent tutoring system (ITS) is a software system that uses artificial intelligence techniques to interact with students and teach them in the same way as a teacher does. The task of dealing with the uncertainty management for the student model is challenging and various approaches in Artificial Intelligence have been proposed for uncertainty reasoning. The paper proposes a Bayesian - Adaptive Neuro-Fuzzy Inference system student model for an ITS. Several models have been developed over time; in a bid to improve the student model accuracy, our paper focuses on using a hybrid of Bayesian inference and Adaptive neuro-fuzzy inference systems as a soft computing technique for creating the desired model. The data gathered were subjected to pre-processing; evaluating the probability values for the questions using the students' cumulative responses. These probability values, question level, students' responses and understanding level formed the data matrix that were trained and tested using the Adaptive Neuro-fuzzy inference system (ANFIS). Our model gave a better prediction accuracy of 79.9% and therefore can be put to use by Intelligent Tutoring Systems for any domain.

General Terms
Artificial Intelligence, ANFIS, Bayesian Inference, Soft Computing, Bloom's Taxonomy

Keywords
Intelligent Tutoring System, Student Modelling, Human Assessment

1. INTRODUCTION
One of the main motivations for research on Artificial Intelligence (AI) in Education is to develop models by which computational learning environments can be designed as places where students can have experiences that are essential and beneficial to them, regardless of their individual differences, previous experiences or other cognitive situations [1]. With the evolution of Artificial Intelligence (AI) techniques and research in the field of cognitive science, increased the degree of "intelligence" of Computer aided Instruction (CAI) systems. They came to be called ICAI (intelligent CAI) and later known as Intelligent Tutoring Systems.

ITS has been designed and developed for providing a rich learning environment in which students can learn actively, freely creating exercises, which allow them to operate and manipulate subject matter concepts[2].

ITS generally supports the theory of "learning by doing" and provides customized instruction to a student while performing a task within a problem domain such as mathematics, medical diagnosis, or even game play. An ITS is organized by an architecture composed by a domain model (what is taught?), student model (who is taught?), instructional model (how is it taught?) and the interface model (man–machine interaction)[3], as in Figure 1.The Student Model contains the description of the knowledge level of the student along with their misconception and knowledge gaps. The goal of student model is to provide adaptive and personalized tutoring to each individual student based on his/her profile.

Student Modelling is the most crucial task of the ITS [4]. ITS must be able to determine accurately and quickly the student cognitive level to decide what is important to teach them. Various approaches in Artificial Intelligence have been proposed for uncertainty reasoning, including ; Rule-based systems , Fuzzy logic, Dempster Shafer theory of Evidence, Neural networks, Bayesian networks, Decision trees, Hidden Markovs model and Genetic Algorithm [5]. This paper discusses an ANFIS model based on Bayesian inference that will effectively manage the uncertainty of students and provide a more accurate prediction technique for student progressive performance. Fuzzy systems can extend the Bayesian inference because they allow users to express prior or likelihood knowledge in the form of if–then rules. They can approximate any prior or likelihood probability density functions and thereby approximates any posterior probability density function. This allows a user to describe priors with fuzzy if–then rules rather than with closed-form probability density functions.

The basic idea for including ANFIS as a type the fuzzy logic in ITS, is to handle the uncertainty of the learner's; when learners believe that they completely understand the concept however, they are not clear with the concepts. Fuzzy set theory allows an object to be a member of a set with a certain degree of membership [6].

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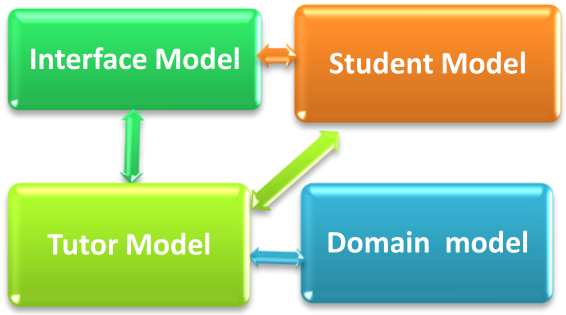

Figure 1. Its Architecture

2. RELATED WORKS

The work by [7] examined the pedagogical effectiveness of a Chinese mathematical dialogue-based intelligent tutoring system used for teaching mathematics. The mathematical unit 'multiplication and division of time expressions' was taught to 134 fifth-grade students in three types of instruction conditions: the intelligent tutoring system (ITS), conventional teacher instruction and material reading. The results show that student performance was comparable between the proposed mathematical ITS and conventional instruction conditions but was significantly poorer when no teaching method was used. Their questionnaire survey showed that the ITS method not only improved maths learning, but also increased motivation among the fifth graders. It was evaluated that, the system attained an accuracy of 73%.

In the paper by [1] on fuzzy logic application in virtual education, the system proposed problems for the students, based on their level of knowledge in the subject matter, their preferences and the level of difficulty of the problem. It also reviewed mechanisms of the problems solved. The evaluation task of these problems was made by using fuzzy logic. For the methodology, it was asked for 60 master's students to solve at least three linear programming problems with different difficulty levels. All the variables were fuzzified after evaluation; the inference process was run on the fuzzy crisp values which were Regular, Good, Very Good and Excellent. The fuzzy results were also defuzzified using the average maximum method to convert the fuzzy response to a numeric value between 0 and 10, corresponding to the degree of accuracy of the problems. The accuracy of this system was evaluated to be about 78.9%.

A Fuzzy inference Intelligent Tutoring System that has two inputs and one output was proposed by [6]. The inputs and the output of the proposed FIS were further divided into sets with clearly defined boundaries that is without a crisp. The fuzzy rule set consists of two input vectors (antecedent) named as "Class Record" and "Exam Performance" based upon which the output vector (consequent) named as "Student Performance" is classified. The input 'Class Record' was divided into three fuzzy sets i.e. outstanding, satisfactory and unsatisfactory. The input 'Exam Performance' was also divided into eight fuzzy sets named as Highest, Higher, High, Above Average, Average, Low, Lower and Lowest. The output vector "student performance" was divided into eight fuzzy sets named as Remarkable, Excellent, Proficient, Fair, Less Fair, Poor, Very poor and Fail. Fuzzy rules were built in an If-then format by taking into consideration the behavior of the system with respect to the antecedent and consequent.The proposed system was evaluated using human assessment and was found to be 72% accurate.

The paper by [8]focused on the probability inference of the Bayesian network to infer the level of knowledge possessed by each student. The inferences were also used to reinforce topics in order to cover the student's needs. Given the positive evidence; it was considered that testing the rest of variables examined in the Bayesian network can provide better accuracy in the diagnostic of student' knowledge possession. The student Evaluation module was tested with a group of undergraduate students. Results showed that it was more efficient and effective than the computer exam and a traditional paper exam. This study proved that those concepts determined as known or unknown have 75.6% of probability.

3. METHODOLOGY

This section clearly shows how our work was carried out. It shows the underlying factors that were considered and the detailed explanation of our work in the subsequent sections. Figure 3.1 shows the pictorial representation of the methodology cycle.

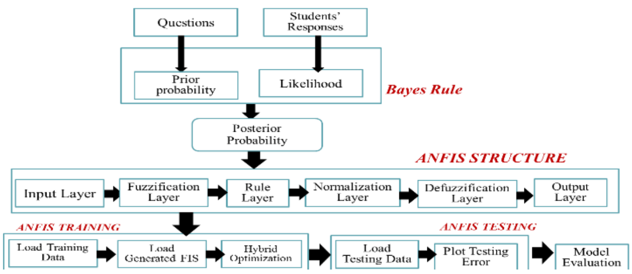

Figure 3.1 Proposed Bayesian ANFIS Model

For the purpose of this paper, the domain considered is Algorithms because of its importance as STEM subject and it forms a very important part of Computer Science curriculum. The concepts and topics in Algorithms are also considered to be broad and explicit. 50 Algorithm questions that covered all identified concepts and topics were put together as Shown in Table 3.1. The level of complexity for each question was assigned using Bloom's Taxonomy for domain classification. The blooms Taxonomy classification ranges from lower to higher levels of cognitive thinking.

3.1 Bayesian Inference

The basis for Bayesian inference is from the Bayes Theorem which is:

$$P(A|B)=\frac{P(B|A)P(A)}{P(B)} \qquad \textbf{Equation 3.1}$$

And this can be rewritten as:

$$P(A|B)=\frac{P(B|A)P(A)}{P(B|A)P(A)+P(B|A^1)(I-P(A))} \qquad \textbf{Equation 3.2}$$

Where;

P(A) = The prior Probability (The hypothesis). In this case, A is the hypothesis that a student gets a question correctly by probability of A (P(A)). A^1 is the hypothesis that a student fails the question.

P(B|A) = The likelihood function. In this case, it is the probability of students' knowledge given a correct answer.

$P(B|A^1)$ = The probability of students' knowledge given a wrong answer.

P(B) = Data (Evidence). In this case, B is responses to each question from the students' samples.

P(A|B) = The posterior Probability. In this case, it is the probability that a question is answered correctly/wrongly.

The prior probability is the initial belief and this was updated with evidences (data) to get the posterior probability. All students already have initial knowledge probability (Prior) which was revalidated and updates taking into accounts the responses to each questions by the help of the Bayes rule.

3.2 ANFIS Structure

The adaptive neuro-fuzzy inference system consists of 6 layers, each layer consisting of nodes that are represented as neurons.As seen in Equation 3.3; the first layer of an Adaptive neuro-fuzzy system is the input layer which consists of input variables represented as neurons. Neurons in this layer pass external crisp values to layer 2.

$$y_i^1 = x_i^1 \qquad \textbf{Equation 3.3}$$

Where $x_i^1$is the input and y_i^1 is the output of inputs i in the layer 1. For our model, we had three (3) input variables which are; Posterior Values (x_1), Question level (x_2), students responses (x_3) and one output variable; Understanding Level Status (x_4).

Neurons in the second layer perform fuzzification. Membership functions were generated from the inputs, membership degrees and parameters are specified for each membership functions. In our model, fuzzification neurons (fuzzy crisp values) for the posterior values had a generalized bell membership function which is specified as:

$$y_i^{(2)} = \frac{1}{1+[\frac{x_i^{(2)} - a_i}{c_i}]^{2b_i}} \qquad \textbf{Equation 3.4}$$

Where x_i^2 is the input and y_i^2 is the output of neuron i in the layer 2; anda_i,b_i and $c_i$are the parameters that control respectively the centre, width and slope of the generalized bell membership function. The other two input parameters Question Level and students' responses have a Gaussian membership function which is specified as;

$$y_i^{(5)} = e^{\frac{-(x_i^{(5)}-c)^2}{2\sigma^2}} \qquad \textbf{Equation 3.5}$$

In Layer three, each neuron corresponds to a single sugeno-fuzzy rule. A rule neuron receives inputs from the respective fuzzification neurons from layer 2 and calculates the firing strength of the rule it represents. The conjunction of the rule antecedents is evaluated by the operator **product.** The output of the rule neuron i in layer 3 is obtained as:

$$y_i^{(3)} = \prod_{j=1}^{k} x_{ji}^{(3)} \qquad \textbf{Equation 3.6}$$

Where x_i^3 is the input and y_i^3 is the output of rule neuron i in layer 3.

In the normalization layer which is layer 4; each neuron receives inputs from all the rule layer neurons (layer 3) and calculates the normalised firing strength of a given rule, which is the ratio of the firing strength of a given rule to the sum of firing strength of all rules. It represents the contribution of a given rule to the final result. The output of neuron i in this layer is expressed as:

$$y^4 = \frac{x_{ii}^4}{\sum_{j=1}^{n} x_{(ji)}^4} = \frac{\mu_i}{\sum_{j=1}^{n} \mu_j} \qquad \textbf{Equation 3.7}$$

Where x_i^4 is the input from neuron j located in layer 3 to the neuron i in layer 4, and n is the total number of rule neurons.

Each neuron in this layer is connected tothe respective normalization neuron from layer 4, and also receives initial inputs;x_1, x_2 and $x_3$from layer 1.A defuzzification neuron calculates the weighted consequent value of a given rule as;

$$y_i^{(5)} = x_i^{(5)}[k_{i0} + k_{i1}x1 + k_{i2}x2] = \bar{\mu}[k_{i0} + k_{i1}x1 + k_{i2}x2]$$

Equation 3.8

Where x_i^5 is the input and $y_i^{\mathbf{5}}$ is the output of the defuzzification neuron in this layer, and k_{10}, k_{i1} and k_{i2} is a set of consequent parameters of rule i.

The last layer of the ANFIS system is represented by a single summation neuron that calculates the sum of outputs of all defuzzification neurons and gives an overall ANFIS output y;

$$y = \sum_{i=1}^{n} x_i^{(6)} = \sum_{i=1}^{n} = \bar{\mu}[k_{i0} + k_{i1}x1 + k_{i2}x2]$$

Equation 3.9

4. RESULT DISCUSSION

The proposed methodology was implemented using MATLAB (MATtrixLABoratory) because it contains powerful and comprehensive tools that can be used for accurate predictions. A uniform prior value of 0.5 was assigned to each questions; this means that each students have an assumed probability value (0.5) of answering each question. This assumption is based on the fact that we are uncertain about each students understanding level of concepts each questions relate. The response from the student can either be correct or incorrect; with an equal probability of 0.5. In order to complete the definition of the Bayesian model, the prior distributions and the Likelihood were approximated.

The likelihood function which contains the available information provided by the sample was evaluated from the responses of the students to each question. This is expressed as the ratio of the correct responses to the total number of responses. The prior value is then multiplied by the likelihood value and thennormalized to estimate the posterior probability distribution, which is the conditional distribution of given the data.

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Question No	LEVEL	LEVEL CODE	Prior Value B	Likelihood	(Likelihood)'	Posterior B
1	Basic	1	0.5	0.66	0.34	0.66
2	Intermediate A	3	0.5	0.538	0.462	0.538
3	Basic	1	0.5	0.796	0.204	0.796
4	Intermediate B	2	0.5	0.706	0.294	0.706
5	Basic	1	0.5	0.327	0.673	0.327
6	Advanced A	5	0.5	0.352	0.648	0.352
7	Advanced A	5	0.5	0.472	0.528	0.472
8	Intermediate A	3	0.5	0.289	0.711	0.289
9	Advanced B	4	0.5	0.604	0.396	0.604
10	Intermediate A	3	0.5	0.143	0.857	0.143
11	Basic	1	0.5	0.667	0.333	0.667

Figure 4.1: Bayesian Inference data

The Adaptive Neuro-fuzzy Inference system (ANFIS) uses the Sugeno method of fuzzy Inference whose output membership functions are either linear or constant.

The first step was to take the inputs and determine the degree to which they belong to each of the appropriate fuzzy sets via membership functions. Our Inputs; Posterior Probability values, Questions level and Students Responses were fuzzified and the degree of membership for each were determined based on the membership functions. The gbellmf (Generalized Bell Shaped Membership Function) was used for our input variable: ***Posterior Probability Value,*** the gaussmf (Gaussian Membership Function) for input variables (***Question level and Student Response),*** the membership function for our output variable was constant. Figs 4.1 and 4.2 shows the implementation of the membership function in MATLAB, the graphical layout represents the membership function plots which displays ranges of value specified for each of the fuzzy crisp value Some of the Input membership functions were implemented as;

Input: Posterior Probability Value.

```
a=addvar(a,'input','posterior',[0.01,0.824]);
```

```
a=addmf(a,'input',1,'low_Posterior','gbellmf'
,[0.10,0.25,0.40]);
```

Input: Question level.

```
a=addvar(a,'input','Question_level', [1,5]);
```

```
a=addmf(a,'input',2,'Basic','gaussmf',[0.1,1]
);
```

Input: Student Response

```
a=addvar(a,'input','student_response',[1,2]);
```

Output: Understanding Level Status

```
a=addvar(a,'output','Understanding_Level_stat
us',[1,5]);
```

```
a=addmf(a, 'output',1,
'Iincrease_level_Basic_int','constant',2);
```

```
a=addmf(a,
'output',1,'Remain_level_Basic1','constant',1
);
```

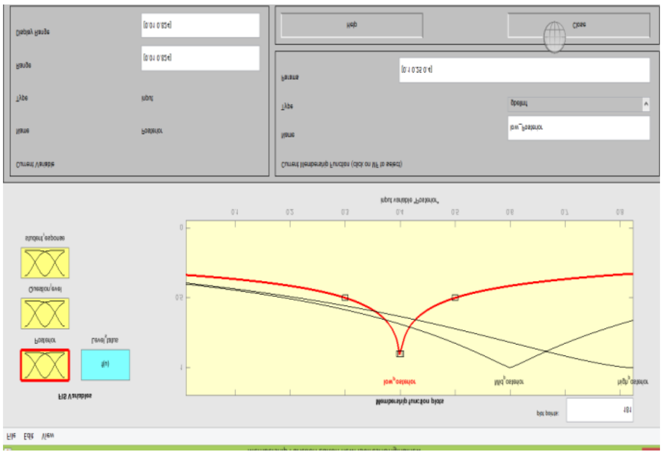

Figure 4.1: Posterior Probability Membership Function plot

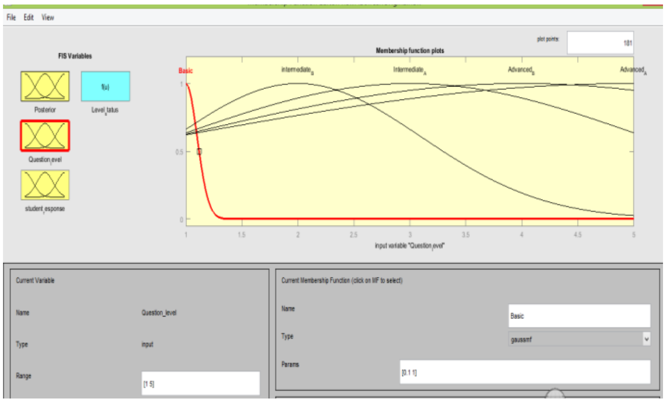

Figure 4.2: Question Level Membership Function Plot

Next is the construction of the fuzzy rules using the (***if then***) clause as,

```
1. If (Posterior is low_Posterior) and
   (Question_level is Basic) and
   (student_response is correct) then
   (Level_status is Remain_level_Basic1)
   (1).
2.  If (Posterior is low_Posterior) and
   (Question_level is intermediate_B) and
   (student_response is correct) then
   (Level_status is Remain_level_intB)
   (1).
3. If (Posterior is low_Posterior) and
   (Question_level is Intermediate_A) and
   (student_response is correct) then
   (Level_status is Remain_level_intA1)
   (1).
4.  If (Posterior is Mid_posterior) and
   (Question_level is Advanced_B) and
   (student_response is correct) then
   (Level_status is Increase_level_AdA1)
   (1).
5. If (Posterior is high_posterior) and
   (Question_level is intermediate_B) and
   (student_response is incorrect) then
   (Level_status is Remain_level_intB2)
   (1).
```

Fig 4.3 shows the rule representation on MatLab with column 1, index 1 representing the value for the membership function associated with input (Posterior probability values). column 1, index 2 representing the value for the membership function associated with input (Question Level), column 1, index 3 representing the value for the membership function associated with input (Student Response), Column 2 representing the value for the membership functions associated with the output (Understanding Level Status), Column $m + n + 1$ (3) as the weight associated with that rule (typically 1) and Column $m + n + 2$ (2) specifies the connective used (AND=1).

PLOTS | VARIABLE | VIEW

1x30 struct with 4 fields

Fields	antecedent	consequent	weight	connection
1	[1,1,1]	2	1	1
2	[2,1,1]	1	1	1
3	[3,1,1]	3	1	1
4	[1,1,2]	4	1	1
5	[2,1,2]	5	1	1
6	[3,1,2]	7	1	1
7	[1,2,1]	6	1	1
8	[2,2,1]	8	1	1
9	[3,2,1]	9	1	1
10	[1,3,1]	10	1	1
11	[2,3,1]	11	1	1
12	[3,3,1]	12	1	1
13	[1,4,1]	13	1	1
14	[2,4,1]	14	1	1
15	[3,4,1]	15	1	1
16	[2,4,2]	16	1	1
17	[1,5,1]	17	1	1
18	[2,5,1]	18	1	1
19	[3,5,1]	19	1	1
20	[1,2,2]	20	1	1
21	[2,2,2]	21	1	1
22	[3,2,2]	22	1	1
23	[1,3,2]	23	1	1
24	[2,3,2]	24	1	1
25	[3,3,2]	25	1	1
26	[1,5,2]	26	1	1
27	[2,5,2]	27	1	1
28	[3,5,2]	28	1	1
29	[1,4,2]	29	1	1

Figure 4.3: Rule Representation in MATLAB

From Fig 4.4; the posterior indicated is 0.152 (Low), the question level is 3(Intermediate B) and student's response is 2 (Incorrect). The resultant output (Level_Status) after the concerned rule was normalised is 2.36 which is approximately 2. This implies that the level of the next question should be lowered for that particular student.

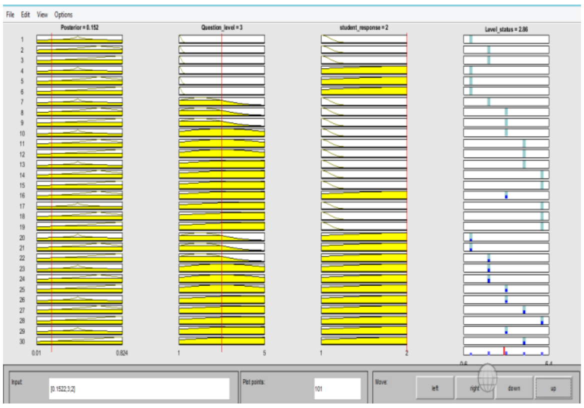

Figure 4.4: Normalized Rules Plot

Lastly, the product of each membership function and the consequent parameter of the normalized rule was done. The initial inputs (Posterior probability value, Question level and student response) are mapped to their corresponding output (Understanding Level status). The basis of this mapping was the product of the resultant antecedent of the input variables and the result of each normalized rule. As shown in Fig 4.5, the fourth layer (outputmf) depicts the defuzzification process of the ANFIS model.

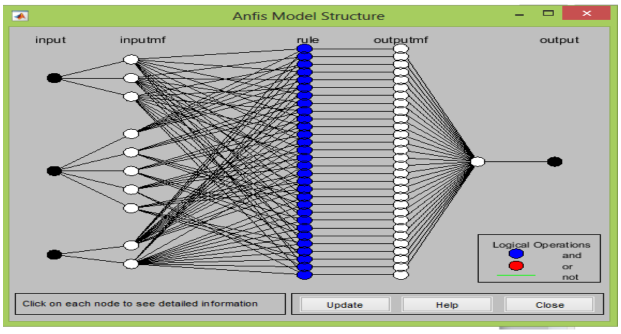

Figure 4.5: ANFIS Model Structure

4.1 Description of Dataset

The dataset for this research were a collation of student responses to a survey on design and analysis of Algorithms; which is our domain. The variables of the data sets were Posterior Probability values, Questions level, Students Responses and Understanding level status. The posterior probability values range between 0-1, The students' responses were represented as 1 (correct) and 2 (incorrect), The question levels were represented with integer values 1, 2, 3, 4, 5 for Basic, Intermediate B, intermediate A, Advanced B and Advanced A respectively. The Understanding level status which is the output variable were a variation from 1-5 which specified either and increase or decrease in question levels or remaining on level the same for a particular student. A total of 2750 data specifically 55 responses to 50 questions were gathered for the research.

The Adaptive Neuro Fuzzy Inference system model developed was trained with 2000 data sets and tested with 750 data sets. This was carried out using the anfis command of the fuzzy logic toolbox available on the MATLAB.

4.2 Dataset Training

The file containing the training data set and the afore generated Fuzzy Inference System were loaded in to the Matlab with ***load*** and ***readfis*** functions. A hybrid optimization method comprising of backward propagation and least squares was used to train the membership function parameters to emulate the training data. The number of training epoch used is 50 and was specified as; epoch_number = 50. A checking data set, chkData, was used for cross validating and testing the generalization capability of the fuzzy inference system at each epoch specified.

The training result display Options is also specified as dispOpt = ones(1,4), which means that 4 display options including; display ANFIS information, display error (each epoch), display step-size (each epoch), display final results were set to 1 (enabled).

Fig 4.6 shows the error values plotted against the number of epoch, with the blue plots representing the testing error and the red plot representing the checking error. The checking error chkErr records the Root Mean Square Error for the checking data at each epoch.

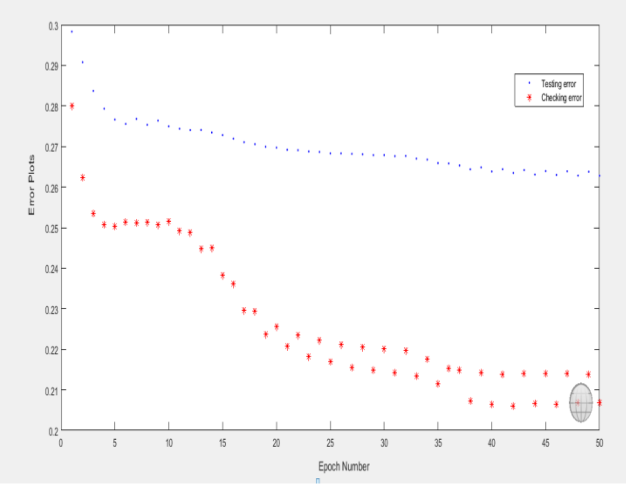

Figure 4.9: Training and Checking Error Plots

4.3 Dataset Testing

In order to validate our model, testing was carried out after training. The testing data set of 750 is loaded with the ***load()*** function.. Fig 4.7 shows the testing data being plotted against the checking data. The purpose of which was to test data sets on which the Fuzzy Inference System was not trained. The data set was presented to the trained FIS model, to see how well the FIS model predicts our corresponding data set output values. The testing error recorded as shown in Fig 4.6 is 0.33507.

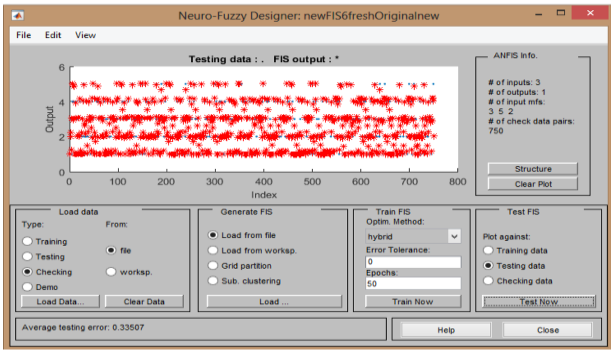

Figure 4.7: GUI Showing Testing Data after Testing

4.4 Bayesian ANFIS Model Evaluation

Fig 4.8 shows the surface plot mapping the posterior value and student response to the level status with the question level at level 3 (Intermediate_A) as the reference input. It can be explained from the plot that as the posterior values tends to its peak with a correct student response, the Level status is also increased to 4 (Advanced_B). The level status will fall back to 2 (Intermediate_B) when the student response is wrong and a low posterior probability value is maintained. A level status at 3 may be maintained when the posterior value is on the average and the student response is correct.

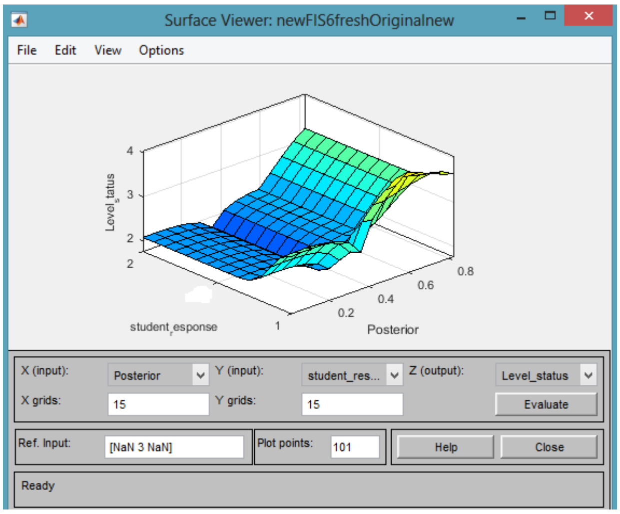

Figure 4.8: Surface Plot Mapping Posterior probability value and student response to Understanding level status

With a student response as a reference input, the Question level will continue to increase on mid and high posterior probability values, thus the understanding level increases. Several curves with different plots and grids were also generated for different input intervals as specified in our input membership functions.

4.5 Comparative Analysis with Existing student modelling Techniques

Table 4.1 and Figure 4.9 shows the comparative analysis of our Bayesian ANFIS student model with the existing Bayesian network and Fuzzy System models. This comparison is drawn from the data sets and prediction accuracy of each technique.

Table 4.1 Comparative Result Analysis

	No of students	No of Data sets	Prediction Accuracy
BAYESIAN ANFIS	55	2750	79.9%
BAYESIAN INF.	62	62	75.6%
FUZZY INF.	100	100	72%

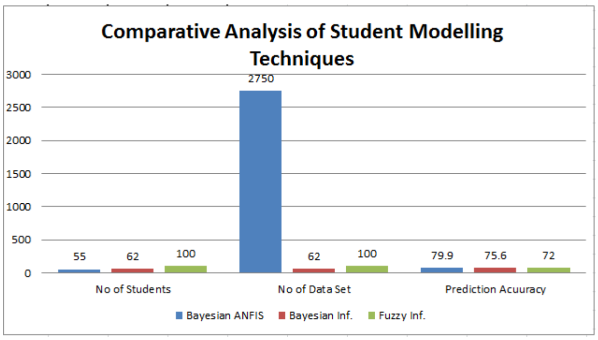

Figure 4.9: Chart showing Comparative Analysis

5. CONCLUSION

This work proposed a soft computing approach to extract knowledge from students' raw data, applying human-like reasoning mechanisms, dealing with uncertainty and imprecision, and learning to adapt to a rapidly changing and unknown environment. In conclusion, the use of an Adaptive Neuro Fuzzy Inference System based on Bayesian inference gave a better prediction accuracy of 79.9% and therefore can be put to use by Intelligent Tutoring Systems for any domain.

6. RECOMMENDATION

The flourish of AI and deep learning techniques offers a foundation for reform in the educational sectors. The implementation of AI and deep learning techniques in the education sector is now changing the industry and has the potential to radically transform the state-of-art of education[9]. As a recommendation, this work can be extended to explore deep learning techniques in order to improve the prediction accuracy of the student understanding level of domain concepts.

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