Prediction of Preclinical Academic Performance using ANFIS Model

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Abstract. ANFIS is a fuzzy inference system integrated into neural networks normally used for pattern recognition and classification purposes. In this work, an ANFIS was designed and used to predict preclinical performance of medical students based on given inputs. The inputs included academic achievements during preclinical, pre-university, and high school. The most significant predictors were found to be a combination of performances across the phases. Accuracy of the prediction was measured in terms of the Root Mean Square Error. The results were as robust as of the linear regression. Thus, the ANFIS model is a good alternative predictive tool.

Keywords: Academic Performance, ANFIS, Prediction, Preclinical.

1. Introduction

Admission to medical school is very competitive throughout the world. Selection of students is done carefully to ensure only highly suitable candidates are chosen to go through the 5 or 6 years of resource-intensive training. The high level of selection followed by rigorous training is required in order to produce competent and safe doctors who deal with human life.

Evidences across the globe are conflicting regarding the predictive values between preadmission grade and performance in medical school [1, 2, 3, 4, 5]. In relation, the main question to answer in this work is to find to what extent the predictive value of performances in pre and post admission to medical school. It is hoped that the findings will help schools to identify best candidates to admit and to reject among those highly competent candidates. Only the correct most students can embark into expensive, rigorous, and long training to become health care professionals.

Fuzzy inference is a neural network integrated system normally used for pattern recognition and classification purposes. The system has successfully been used to explore and model a set of data to discover unknown patterns or relationships and finally provide clear and useful results in various domains [6, 7, 8, 9]. Its algorithm estimates an unknown dependency between a set of given input variables and its response variable. When such dependency is discovered, ANFIS (Adaptive Neuro Fuzzy Inference System) can deduce the output associated with chosen input values. Complementing earlier works, this work designs and implements ANFIS that helps deduce and identify critical predictive factors of students' performance in medical schools. The input variables in this case are prior academic performance encompasses high school, pre-university, and preclinical.

2. Method

2.1. Background

Table 1: Education pathway from high school to MBBS degree

	High School	Pre-University	Preclinical	Clinical
Duration	5 years	3 sem.	4 sem.	6 sem.
Assessment Criteria	# of As across the sciences	CGPA	CGPA after 4 sem.	CGPA after 10 sem.

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This study uses academic results of two batches (i.e. 2007 and 2008 intakes) with a total of 160 students in Cyberjaya University College of Medical Sciences, Malaysia. Students in the program go through four stages of education namely: high school, pre-university, preclinical, and clinical in order to graduate with a Bachelor of Medicine and Bachelor of Surgery (MBBS). Table 1 summarizes the pathway to MBBS degree.

The developed ANFIS is a multi-input single-output system with 13-input and 1-output attributes. The input attributes include high school exit examination result consisting of 2 languages (Malay and English) and 5 sciences (Mathematics, Additional Mathematics, Physics, Chemistry, and Biology); number of As across the science subjects; cumulative grade point average (CGPA) of pre-university; and grade point average (GPA) of four consecutive semesters in preclinical phase. The output is the CGPA at the end of preclinical year. These imprecise attributes are called fuzzy linguistic variables and expressed by fuzzy linguistic labels such as average (A_1), good (A_2), and excellent (A_3). The input and output attributes are summarized in Table 2.

Table 2: Input and output attributes for ANFIS and Linear Regression models to predict preclinical performance.

Input	Output
Malay (BM)	CGPA Preclinical (cgP)
English (BI)	CGPA Preclinical (cgP)
Math	CGPA Preclinical (cgP)
Add. Math. (AMath)	CGPA Preclinical (cgP)
Physics (Phy)	CGPA Preclinical (cgP)
Chemistry (Chem)	CGPA Preclinical (cgP)
Biology (Bio)	CGPA Preclinical (cgP)
# of As across the sciences (#A)	CGPA Preclinical (cgP)
CGPA Pre-university (cgF)	CGPA Preclinical (cgP)
GPA Pre-clinical Sem. 1 (S1)	CGPA Preclinical (cgP)
GPA Pre-clinical Sem. 2 (S2)	CGPA Preclinical (cgP)
GPA Pre-clinical Sem. 3 (S3)	CGPA Preclinical (cgP)
GPA Pre-clinical Sem. 4 (S4)	CGPA Preclinical (cgP)

2.2. Procedure

The data set was divided into training (50%) and checking (50%) data sets. The training data set was used to create the ANFIS model while the checking data set was used to validate it. The model was capable of: deciding on the fuzzy partitions of the input/output spaces; defining input/output variables; deciding on the types of fuzzy control rules; designing the inference mechanism; choosing a de-fuzzification procedure and; choosing the best input-output relationship. The research methodology is summarized in Fig. 1.

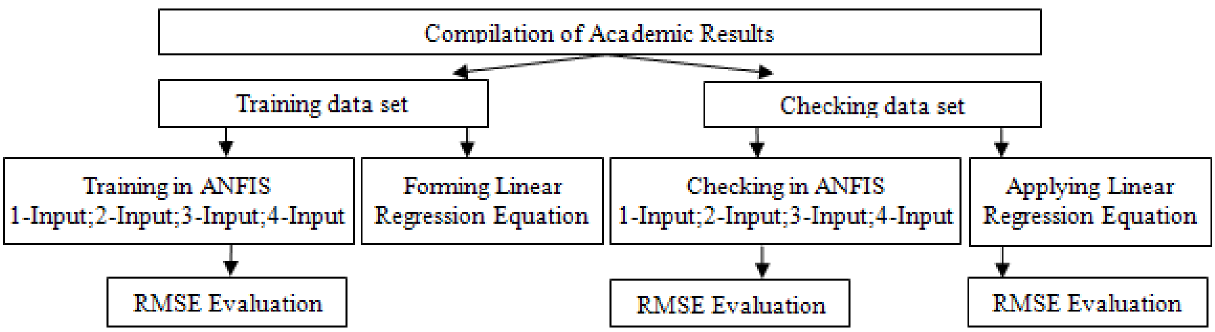

Fig. 1: Summary of the research methodology.

For comparison purpose, a linear regression model was also developed using similar inputs as in ANFIS. Both prediction models' accuracies were compared in terms of the Root Mean Square Error (RMSE) as in (1), where A_t and F_t are actual and fitted values respectively and N is the number of sample [10].

$$RSME = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(A_t - F_t)^2} \qquad (1)$$

3. Fuzzy Reasoning, Fuzzy Rules, and Membership Functions

Fuzzy rules and reasoning are the main features of fuzzy inference [11]. Fuzzy reasoning derives conclusions from the set of fuzzy IF-THEN rules and known facts. For example, 'IF #A is Excellent, cgF is Average, S1 is Average, and S4 is Good, THEN cgP is Excellent' is a complete rule defining the relation of input and output linguistic variables. The following example of rule set illustrates the reasoning mechanism and the corresponding equivalent ANFIS architecture.

Rule 1: If #A is A_3 and, cgF is A_1 and, S1 is A_1 and, S4 is A_2 then, $f_1 = p_1\#A + q_1 cgF + r_1 S1 + s_1 S4 + t_1$

Rule 2: If #A is A_2 and, cgF is A_2 and, S1 is A_1 and, S4 is A_2 then, $f_2 = p_2\#A + q_2 cgF + r_2 S1 + s_2 S4 + t_2$

Rule n: If #A is A_1 and, cgF is A_3 and, S1 is A_1 and, S4 is A_2 then, $f_n = p_n\#A + q_n cgF + r_n S1 + s_n S4 + t_n$

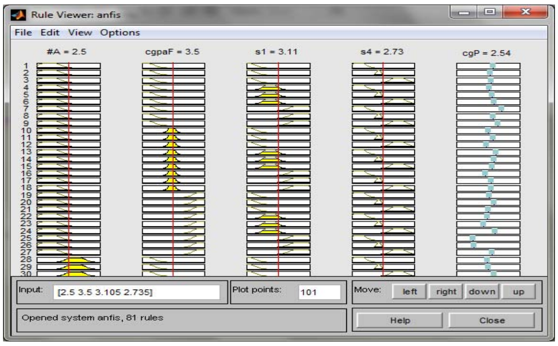

Fig. 2: Fuzzy reasoning procedure model.

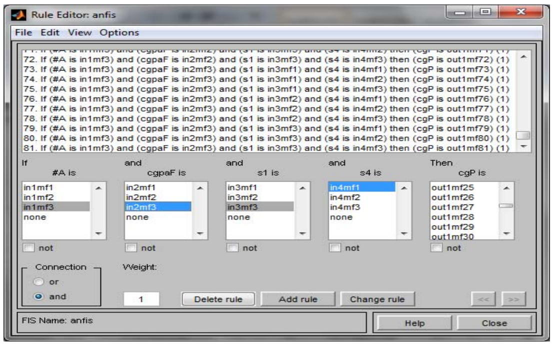

Fig. 3: IF-THEN fuzzy rules derived by ANFIS.

Figs. 2 and 3 show the reasoning procedure for a first order Sugeno fuzzy model. Each rule has a crisp output and the overall output is a weighted average. The ANFIS structure utilizes fuzzy clustering of the input and output data sets as well as the bell-shape membership function (MF). Thus the number of rules equals to the number of output clusters.

4. Architecture of Hybrid Learning and ANFIS

Fig. 4 shows the architecture of 4-input 1-output ANFIS structure. The computation of MF parameters is facilitated by a gradient descent vector. The parameters are adjusted as to reduce the error measure defined by the sum of the squared difference between the actual and desired output.

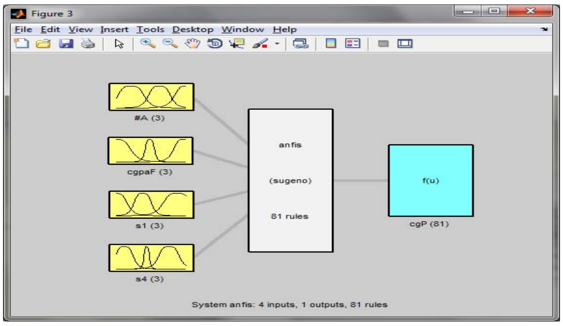

Fig. 4: 4-input 1-output ANFIS architecture model.

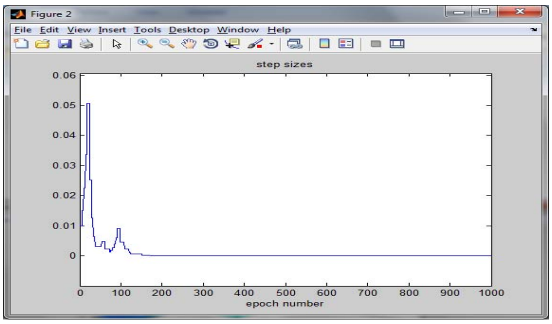

Fig. 5: ANFIS training converges after 200 epochs.

The parameters associated with MFs changes through the learning process of artificial neural network. ANFIS algorithm as proposed by Jang [11] consists of 5 layers as described below.

Layer 1: Every node in layer i is an adaptive node with a function. The output of the ith node is given in (2).

$$O^1_{A_i} = \mu_{A_i}(m), \qquad i = 1,2,3$$

$$O^1_{B_j} = \mu_{B_j}(m), \qquad j = 1,2,3 \tag{2}$$

where *m* and *n* are the inputs to node *i* and $A_1,\ldots,A_i$ are the linguistic labels associated with this node such as average, good, and excellent. $O^1_{A_1}$ is the membership grade of fuzzy set $A_1,\ldots,A_i$. It denotes the degree to which the given inputs *m* or *n* satisfies the quantifier A_i. The membership grade is calculated using (3).

$$\mu_{A_i}(x) = \frac{1}{1 + (\frac{x - c_i}{a_i})^{2b_i}}, \quad i = 1,2,3 \tag{3}$$

where $\{a_i, b_i, c_i\}$ is the parameter set of a bell-shape figure. The parameter is referred as premise parameter [8].

Layer 2: Every node in this layer is a fixed node and the output is the product of all incoming signals as in (4).

$$O^2_{ij} = w_{ij} = \mu_{A_i}(m)\mu_{B_j}(n), \quad i,j = 1,2,3 \tag{4}$$

Each node of output represents the firing strength of a rule.

Layer 3: Every node in this layer is fixed. The node in this layer normalizes the weight functions by calculating the ratio of the *i*th rule's firing strength to the sum of all rules' firing strengths using (5).

$$O^3_{ij} = \overline{w}_{ij} = \frac{\overline{w}_{ij}}{w_{11} + w_{12} + w_{21} + w_{22}} \qquad i,j = 1,2,3 \tag{5}$$

Layer 4: The nodes in this layer are adaptive nodes. The output of this layer is represented as in (6).

$$O^4_{ij} = \overline{w}_{ij} f_{ij} = \overline{w}_{ij}(p_{ij}x + q_{ij}y + r_{ij}) \qquad i,j = 1,2,3 \tag{6}$$

where w_i is a normalized firing strengths from Layer 3 and $\{p_i, q_{i,\ldots,} r_i\}$ are the set of consequent parameters.
Layer 5: The single node in this layer computes the overall output. The output is calculated using (7).

$$O^5_{ij} = \sum_{i=1}^{2}\sum_{j=1}^{2} \overline{w}_{ij} f_{ij} = \sum_{i=1}^{2}\sum_{j=1}^{2} \overline{w}_{ij}(p_{ij}x + q_{ij}y + r_{ij}) \tag{7}$$

The 5 layers of algorithm were applied to the student data set whereby the output was the CGPA of preclinical year. The ANFIS model was first trained using the training data set, and then validated using the checking data sets. ANFIS training was found to converge after 200 epochs as recorded in Fig. 5.

5. Finding and Analysis

It is interesting to note that both ANFIS and linear regression produced the same combinations of best predictors for all the 1-input, 2-input, 3-input, and 4-input variables. They found best 1-input, 2-input and 3-input consisted mainly of students academic performance during pre-clinical semesters. However, when 4-input model was considered then the number of As across the science subjects of high school exit examination and pre-university CGPA were found to be critical.

RMSE comparison works showed that the ANFIS training, linear regression, and ANFIS checking models produced smallest, in between, and largest values respectively. The findings are summarized in Table 3.

Table 3: Best predictors by ANFIS and linear regression for the prediction of Preclinical CGPA and their RMSE values

# of Input	Best Input Predictor Set	RMSE ANFIS		RMSE Linear Regression
		Train.	Check.	
1	Sem. 2	0.0967	0.1384	0.1355
2	Sem. 2; Sem. 3	0.0536	0.2493	0.0833
3	Sem. 1; Sem. 3; Sem. 4	0.0139	1.2850	0.0593
4	# of As across the sciences; pre-university CGPA; Sem. 1; Sem. 4.	0.0000	0.5989	0.1096

6. Discussion and Conclusion

This paper describes the development of a data driven ANFIS model using real data set consisted of students' achievements in their high school, pre-university, and pre-clinical years. The model is a soft computing approach utilizing a feed-forward multilayer neural network for fuzzy modeling. As been shown the model fulfils prediction-modelling requirements which are ability to: explain the prediction outcomes transparently and produce high prediction performance [12]. In fact, training wise, the ANFIS model produced the least value of error.

Although the work answered the main research question, it was however done in limited circumstances. The training was done with a set of 80 students, and the model was validated on the remaining set of 80 students. Cross sectionals validation or multiple arrangements of 80 students might produce better result especially in the RMSE values. In addition, bigger population would have contributed to better recognition of pattern and classification.

Though statistical models have long been used in studying predictor and predicted output relationships, this study shows that ANFIS models are highly robust and compatible. The ANFIS model which are solely based on data pattern and their relationships are found to have good ability in predicting students' academic performance leading to clinical years. The model also shows that overall performance in science during high school and overall performance during pre-university are important determinants to students' selection. In short, this study shows that ANFIS is a suitable artificial intelligent tool for measuring students' academic performance thus provides a good alternative to existing techniques.

7. Acknowledgment

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8. References

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