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Risk Status Prediction and Modelling Of Students' Academic Achievement - A Fuzzy Logic Approach

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ABSTRACT: *Several students usually fall victims of low grade point at the end of their first year in the institution of higher learning and some were even withdrawn due to their unacceptable grade point average (GPA); this could be prevented if necessary measures were taken at the appropriate time. In this paper, a model using fuzzy logic approach to predict the risk status of students based on some predictive factors is proposed. Some basic information that has some correlations with students' academic achievement and other predictive variables were modelled, the simulated model shows some degree of risk associated with their past academic achievement. The result of this study would enable the teacher to pay more attention to student's weaknesses and could also help school management in decision making, especially for the purpose of giving scholarship to talented students whose risk of failure was found to be very low; while students identified as having high risk of failure, could be counselled and motivated with a view to improving their learning ability.*

KEYWORDS: *fuzzy logic, academic achievement, prediction and risk status.*

I. INTRODUCTION

In the institution of higher learning, several students are found of having low grades while they are in first year; findings reported in [5] revealed that, stress during this period is associated with overall academic adjustment and low GPA. Modeling of student's achievement is a useful tool for both educators and students, as this can help to have better understanding of student's weakness and bring about enhancement [8]. First year students needs some form of monitoring especially as regards to their academic performance. Modelling the past academic achievement in order to establish the risk of students' failure based on some information they earlier submitted for admission purposes is a step in the right direction, though, a challenging task. According to [10], working with uncertain information makes estimation with the actual number value difficult, but this could be easily understood if done with natural language. Fuzzy logic technique (FLT) provides efficient and feasible solutions by following the input output system represented in Fig 2. The knowledge of fuzzy logic is most suitable according to [11], when modelling of human evaluation is needed. Also, in [19], it was reported that FLT is the most important technique to handle imprecision and uncertainty. It is of paramount importance to evaluate students' achievement after the students complete their registration as such exercise would enable the teachers to offer assistance to them for better performance. Knowing fully well that education is very essential and inevitable for the upliftment and progress of a nation [1], all hands must always be on deck to make it promising.

The objective of this paper was to explore the students' academic achievement of newly admitted students with a view to classifying their risk status using fuzzy logic technique. The rest of this paper is organised as follows: Some related works reported in literature on prediction of student's performance were discussed in the next section; in section 3, we discussed briefly about fuzzy logic concept and its basic operations; while in section 4, we present the design, analysed the method used and display our results; discussion of results is in section 5 and the whole work is concluded in section 6.

II. RELATED WORKS

Several classification algorithms have been applied to predict students' academic achievements, in the process, the levels of accuracies were measured; however, most of these methods are subjective. It is important to predict students' performance in order to differentiate between the fast learners and slow learners as observed in [9]. It was revealed in their findings that, students' academic performance should not depend on their own efforts alone, relevant predictive factors were also identified. A comparative analysis of techniques for predicting academic performance was proposed in [2], models were constructed using weka tool, a very high accuracy was reported and diverse grading systems was identified as the difficulty encountered in the course of applying the technique to international students. The academic predictors were measured in [3] to determine their accuracy and efforts were made at establishing their level of reliability most especially at discriminating from success and failure cases of classifier or predictive model. Research conducted in [5] shows that mature-age students achieved higher final degree GPA compared to young undergraduates. Though, this may be environment specific.

Achievement evaluation model reported in [4] proposed Radial Basis Function Neural Network and similarity filter to evaluate learning achievement, three phases that can reduce bias assessment were identified, these include: selection of important feature attributes to enhance classification performance, using of minimal entropy principle approach to fuzzify the quantitative data, model construction and accuracy evaluation.
Genetic fuzzy approach was proposed in [19] to identify students' skills. The idea to combine the two techniques was to explore soft computing techniques that support learning and evolution. Rules for identifying some intelligence were generated for the achievement and powerful classification of human capabilities. Also, in a survey carried out on Fuzzy Inference-Based student evaluation methods in [17], five different evaluation methods capable of unveiling students' achievement were identified; these include: Fuzzy Classification, Bai-and-Chen's Method, Saleh-and-Kim's Method, Fuzzy Rule Interpolation and Rasmani-and-Shen's Method. It was concluded that Fuzzy inference based solutions offer a transparency result due to the humanly interpretable rules. Evaluation of students' performance using data-driven fuzzy rule was proposed in [6], the approach was reported to perform Norm-Referenced Evaluation which produced new and informative scores based on several information retrieved from data. It was concluded that the findings was meant to help strengthen the system that is commonly in use, as the approach was intended to provide additional information for decision making.

III. FUZZY LOGIC

Fuzzy logic (FL) can be described as logic of fuzzy sets [13]. It is an area of soft computing that enables a computer system to reason with uncertainty [16]. The concept was initially formalized by Lofti Zadeh in his seminar 1965 paper "Fuzzy sets". A fuzzy set is distinct from a crisp or Boolean set because it allows its elements to have a degree of membership i.e the characteristics function of a fuzzy set can have values between 0 and 1 [15]. The core of a fuzzy set is its membership function: a surface or line that defines the relationship between a value in the set's domain and its degree of membership [13].Fuzzy logic according to [12] has two different meanings: It can be referred to as a logical system which may be viewed as an extension and generalization of classical multi-valued logics. In a wider sense, FL is almost synonymous with the theory of fuzzy sets as any field X and any theory Y can be fuzzified by replacing the concept of a crisp set in X and Y by that of a fuzzy set [12]. The fuzzy linguistics variable "risk" can be categorized as: very low, low, medium, high and very high. Each category is called a linguistic modifier. The modifier can take its degree of membership from [0, 1] as shown in figure 3. The scales on this figure are used to distinguish the prediction of students' academic achievement risk (very low risk, low risk, medium risk, high risk and very high risk).

IV. DESIGN AND METHODS

4.1 Dataset and Data Preparation

Getting rid of errors and outliers that may be present in the data are parts of pre-processing task that should be done to make the data suitable for modelling. In many real-world applications, most especially in cases when it involves huge amounts of data, the subset of cases with complete data may be relatively small. Errors can result from data entry mistakes, transposing digits or specifying invalid dates; too much noise can result in poor quality models [17]. The dataset was collected from a university in north central, Nigeria. The data comprised of 37 records of candidates that were offered admission to study Computer Science. TABLE 1 contains the predictive variables, while Fig. 1 shows data preparation using rapidminer tool.

Table 1: The predictive variables

S/NO	INPUT VARIABLE	DESCRIPTION	OPTIONS	VALUES OBTAINABLE
1	SSRS	Secondary School Result Strength	A1;A2;A3;B2;B3;C4;C5;C6	1-6
2	NSSSE	Number of sittings in secondary school examination	1 attempt ; 2 attempts	1-2
3	EM	Entry mode	Utme 1 Remedial 2	1-2
4	PLS	Parent literacy status	Literate 1 Illiterate 2	1-2

5	OSSA	Ownership of secondary school attended	Private 1 Public 2	1-2
6	LSSA	Location of secondary school attended	Town 1; City 2; Village 3	1-3
7	SOJE	Score obtained in Unified Tertiary Matriculation Examination.	Above 250 1 221 – 250 2 200 – 220 3 Below 200 4	1-4

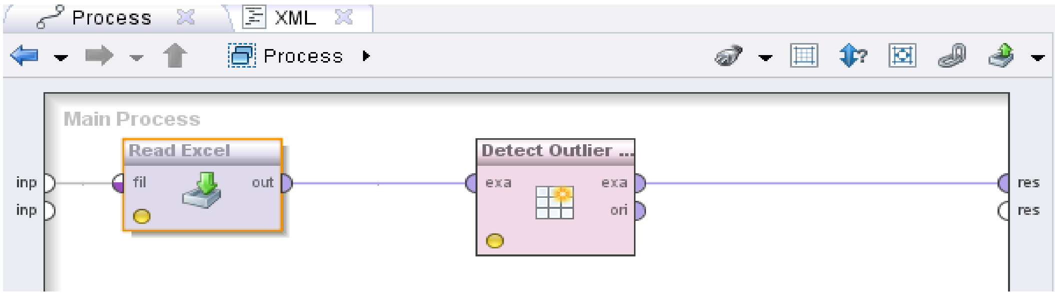


Figure 1: Data cleaning

Table 2 Transformed students' data

CASE	SSRS	NSSSE	EM	PLS	OSSA	LSSA	SOJE
1	4	1	1	1	2	3	2
2	2	1	1	2	2	1	1
3	3	1	1	1	2	1	2
4	5	1	1	1	1	2	1
5	5	1	1	1	2	2	1
6	3	1	1	2	2	3	3
7	4	1	1	1	2	2	2
8	3	1	1	1	2	2	1
9	3	1	2	1	2	3	3
10	4	1	1	1	2	1	2
11	3	1	1	1	1	2	1
12	6	1	2	2	2	1	2
13	3	1	1	1	2	3	1
14	4	1	1	2	1	1	3
15	6	1	1	2	1	2	1
16	4	1	1	2	2	1	2
17	4	1	2	1	2	1	2
18	4	1	2	1	2	1	2

CASE	SSRS	NSSSE	EM	PLS	OSSA	LSSA	SOJE
19	3	1	1	1	1	1	2
20	4	1	1	1	1	2	1
21	4	1	1	1	1	2	1
22	4	1	2	2	1	2	2
23	4	1	1	1	1	2	2
24	6	2	1	2	2	2	1
25	4	1	1	1	2	2	2
26	4	1	1	2	1	2	2
27	6	1	1	2	2	1	2
28	3	2	1	1	2	3	3
29	5	1	1	1	2	2	2
30	5	1	1	1	2	2	2
31	7	2	2	1	1	2	3
32	4	2	1	1	2	1	2
33	6	2	1	2	2	3	1
34	7	2	1	1	1	2	1
35	4	1	1	1	2	2	1
36	4	1	1	2	2	2	1
37	5	2	1	1	2	2	2

As shown in TABLE 2, the individual student's data were transformed based on the options and obtainable values in TABLE 1.

4.2 Analysis of fuzzy set structure and operations

If X is a collection of objects denoted generically by x, then a "fuzzy set" A in X is defined as a set of ordered pairs [15]:

$$A = \{x, \mu_A(x) \mid x \in X\} \ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

Where $\mu_A(x)$ is called membership function for the fuzzy set A which maps each element of X to a membership value between 0 and 1. Element x may have full, partial or no membership in A. Its degree of membership would be considered to be full if $\mu_A(x) = 1$; partial, if $\mu_A(x)$ lies between 0 and 1 i.e $0 < \mu_A(x) < 1$; and no

membership exist if $\mu_A(x) = 0$. As illustrated in Fig. 3, a fuzzy set is formed when a linguistic variable combines with a linguistic modifier (i.e. very low_risk, low_risk, high_risk, medium_risk etc). Each linguistic modifier is linked to a numerical value on a scale ranges from 0 to 9 that represents the academic achievement risk. Also, each element represents a corresponding value of a degree of membership in the universe of discourse. Fuzzy sets can be manipulated using one of the four standard fuzzy set operations: union, intersection, complementation, and implication operations [14]. Though, the set operations discussed here are often used, fuzzy set operations are not limited to this four. A fuzzy set union is performed by applying the maximum (Max) function to the elements of two sets, for instance,
let $\mu_A(x) = \{1,3,5,8,9\}$ and $\mu_B) = \{1,7,4,8,9\}$
the union of fuzzy set $C = A \cup B$; it follows that:

$\mu_C(z) = \mu_A(x) \cup \mu_B(y) = \text{Max}\ \{\ \mu_A(x)\ ,\ \mu_B\ (y)\}$
$\mu_C(z) = \{1,7,5,8,9\}$.

The intersection of two sets can be determined by applying the minimum (Min) function:
$\mu_A(x) \cap \mu_B(y) = \text{Min}\ \{\ \mu_A(x)\ ,\ \mu_B\ (y)\} = \{0,4,1,0,0\}$

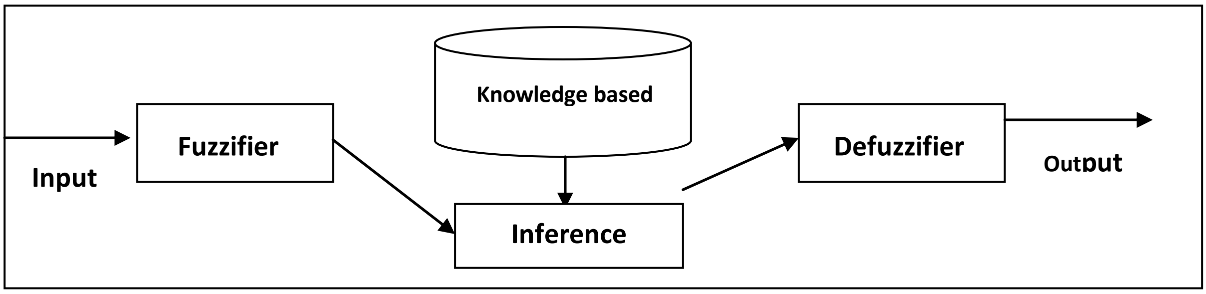
Complement of a set is can be computed by subtracting each element of the set from its maximum possible value:
$\mu_{\bar{A}}(x) = \{9 - \mu_A(x)) = \{8,6,4,1,0\}$

The implication function decides if a particular set is true, to what extent can we conclude the other set can be said to be true? To illustrate implication operation, we can compute:

$$\mu_{\bar{A}} \cup \mu_B\ (q) = \mu_{\bar{A}}(x) \cup \mu_B(y)$$
$$\mu_{\bar{A}} \cup \mu_B\ (q) = \{8,6,4,1,0\} \cup \{1,7,4,8,9\} \quad = \{8,7,4,8,9\}$$

4.3 Proposed model for academic achievement risk status

Due to vagueness in grading educational system, according to [18], the use of fuzzy theory provide better models of subjective judgment. This approach essentially involves three main tasks: fuzzification, inference and defuzzification as represented in Fig. 2. Excerpt of 37 records from the data collected were modelled and a fuzzy set A was formed. The set takes its values from {X} in a closed interval [0,1]. From equation 1 and degree of membership in Fig. 3, $fA(x) = \{0.1, 0.2, 0.4, 0.5, 0.8, 1\}$



There are different forms of membership functions, here we used trapezoidal to illustrate the membership function. According to [15], a trapezoidal membership function is specified by four parameters {a,b,c,d} as shown in equation 2:

Figure 2 Input /Output of a fuzzy logic system

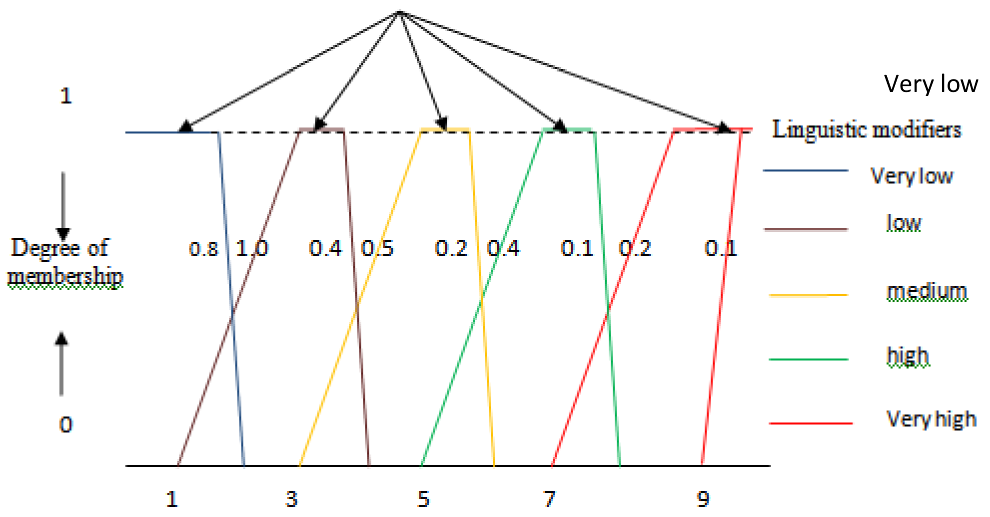


Figure 3 Fuzzy set structure for risk status

The parameters {a,b,c,d} with a < b < = c < d, determine the x coordinates of the four corn high lying trapezoidal membership function.

Trapezoid (x; a,b,c,d) =

$$\begin{cases} 0, & x <= a. \\ (x-a) / (b-a), & a <= x <= b. \\ 1, & b <= x <= c. \qquad \ldots\ldots\ldots(2) \\ (d-x) / (d-c), & c <= x <= d. \\ 0, & d <= x. \end{cases}$$

Table 3 Predictive variables and degree of membership

Predictive variable	Membership value *f*B(y)	Representation (y)
SSRS	0.8	V1
NSSSE	0.5	V2
EM	0.4	V3
PLS	0.6	V4
OSSA	0.7	V5
LSSA	0.6	V6
SOJE	1.0	V7

37 students were considered in this research and the researchers evaluated 7 predictive factors on which predictions were based. From the data displayed in TABLE 3, a fuzzy set B was formed and it takes its values from the closed interval [0,1]. Also from equation 1,

$$B = \{y, \mu_B(y) \mid y \in Y\} \ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

fB(y) = {0.8, 0.5, 0.4, 0.6, 0.7, 0.6, 1.0} as shown in TABLE 3. The table also shows the membership values assigned to each predictive variable which translates to its predictive relevance. Linguistic variables were mapped to corresponding fuzzy values which results to another set as shown in equation 4:

$$C = \{y, \mu_A(y)) \mid y \in Y\} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(4)$$

fC(y) = {0.1, 0.2, 0.5, 0.8, 1.0} as shown in TABLE 4.

Table 4 Fuzzy linguistic variables and membership values

Linguistic variables	Fuzzy values	Relative importance
Very low risk	0 <= x<= 2	1.0
Low risk	1 <= x<= 3	0.8
Medium risk	2 <= x<= 5	0.5
High risk	4 <= x<= 7	0.2
Very high risk	6 <= x<= 9	0.1

As shown in Figure 3 and TABLE 4, the five fuzzy sets can be interpreted as follows:

Very low risk : {1|1.0, 2|0.8, 3|0.0, 4|0.0, 5|0.0, 6|0.0, 7|0.0, 8|0.0, 9|0.0}

Low risk : {1|0.6, 2|0.8, 3|0.5, 4|0.0, 5|0.0, 6|0.0, 7|0.0, 8|0.0, 9|0.0}

Medium risk : {1|0.0, 2|0.3, 3|0.5, 4|0.4, 5|0.0, 6|0.0, 7|0.0, 8|0.0, 9|0.0}

High risk : {1|0.0, 2|0.0, 3|0.0, 4|0.4, 5|0.4, 6|0.2, 7|0.2, 8|0.0, 9|0.0}

Very high risk : {1|0.0, 2|0.0, 3|0.0, 4|0.0, 5|0.0, 6|0.2, 7|0.2, 8|0.1, 9|0.1}

The technique of fuzzy set addresses the representation of parameters using linguistic variables [7], it also provides dynamic framework to handle qualitative information especially when quantitative seems inappropriate. Through the process of fuzzification, we find the membership value of all the input values in TABLE 2, these values were transformed to form another set as shown in TABLE 5. From TABLE 5, the researchers formed 37 fuzzy sets $fc_1(y)$, $fc_2(y)$………$fc_{37}(y)$ that takes its membership values from [0,1]. This process of reduction otherwise known as defuzzification [13] produced the final single scaler results shown in TABLE 6, the table displayed the risk status of all the students (37 cases).

$fc_1(y)$ = {0.5, 1.0, 0.8, 1.0, 0.8, 0.5, 1.0}

$fc_2(y)$ = {0.8, 1.0, 0.8, 0.8, 0.8, 1.0, 1.0}

$fc_{37}(y)$ = {0.5, 0.8, 0.8, 0.5, 0.8, 0.8, 1.0}

Table 5 The academic achievements of all the 37 students

CASE	V1	V2	V3	V4	V5	V6	V7
1	0.5	1.0	0.8	1.0	0.8	0.5	1.0
2	0.8	1.0	0.8	0.8	0.8	1.0	1.0
3	0.8	1.0	0.8	1.0	0.8	1.0	1.0
4	0.5	1.0	0.8	1.0	1.0	0.8	1.0
5	0.5	1.0	0.8	1.0	0.8	0.8	1.0
6	0.8	1.0	0.8	0.8	0.8	0.5	0.8
7	0.5	1.0	0.8	1.0	0.8	1.0	1.0
8	0.8	1.0	0.8	1.0	0.8	0.8	1.0
9	0.8	1.0	0.5	1.0	0.8	0.5	0.8
10	0.5	1.0	0.8	1.0	0.8	1.0	1.0
11	0.8	1.0	0.8	1.0	1.0	0.8	1.0
12	0.2	1.0	0.5	0.8	0.8	1.0	1.0
13	0.8	1.0	0.8	1.0	0.8	0.5	1.0
14	0.5	1.0	0.8	0.8	1.0	1.0	0.8
15	0.2	1.0	0.8	0.8	1.0	0.8	1.0
16	0.5	1.0	0.8	0.8	0.8	1.0	1.0
17	0.5	1.0	0.5	1.0	0.8	1.0	1.0
18	0.5	1.0	0.5	1.0	0.8	1.0	1.0
19	0.8	1.0	0.8	1.0	1.0	1.0	1.0
20	0.5	1.0	0.8	1.0	1.0	0.8	0.8
21	0.5	1.0	0.8	1.0	1.0	0.8	0.8
22	0.5	1.0	0.5	0.8	1.0	0.8	1.0

23	0.5	1.0	0.8	1.0	1.0	0.8	1.0
24	0.2	0.8	0.8	0.5	0.8	0.8	0.8
25	0.5	1.0	0.8	1.0	0.8	0.8	1.0
26	0.5	1.0	0.8	0.5	1.0	0.8	1.0
27	0.2	1.0	0.8	0.5	0.8	1.0	1.0
28	0.8	0.8	0.8	1.0	0.8	0.5	0.8
29	0.5	1.0	0.8	1.0	0.8	0.8	1.0
30	0.5	1.0	0.8	1.0	0.8	0.8	1.0
31	0.2	0.8	0.5	1.0	1.0	0.8	0.8
32	0.5	0.8	0.8	1.0	0.8	1.0	1.0
33	0.2	0.8	0.8	0.5	0.8	0.5	0.8
34	0.2	0.8	0.8	1.0	1.0	0.8	0.8
35	0.5	1.0	0.8	1.0	0.8	0.8	0.8
36	0.5	1.0	0.8	0.5	0.8	0.8	0.8
37	0.5	0.8	0.8	0.5	0.8	0.8	1.0

By applying the Min function to the degree of membership displayed in TABLE 5, we arrived at the decision on the risk status of individual case as shown in TABLE 6.

Table 6 The risk status of all the students

CASE	VALUES	RISK STATUS
1	0.5	medium
2	0.8	low
3	0.8	low
4	0.5	medium
5	0.8	low
6	0.5	medium
7	0.5	medium
8	0.8	low
9	0.5	medium
10	0.5	medium
11	0.8	low
12	0.2	high
13	0.5	medium
14	0.5	medium
15	0.2	high
16	0.5	medium
17	0.5	medium
18	0.5	medium
19	0.8	low

CASE	VALUES	RISK STATUS
20	0.5	medium
21	0.5	medium
22	0.5	medium
23	0.5	medium
24	0.2	high
25	0.5	medium
26	0.5	medium
27	0.2	high
28	0.5	medium
29	0.5	medium
30	0.5	medium
31	0.2	high
32	0.5	medium
33	0.2	high
34	0.2	high
35	0.5	medium
36	0.5	medium
37	0.5	medium

V. DISCUSSION OF RESULTS

TABLE 6 shows the risk status of all the 37 students.The analysis of the results revealed three clusters of students as regards their risk status. Information from the result also shows that, 24 of the students were predicted to have medium risk; 6 of the students were predicted to have low risk; there is no need to exercise any fear about the future performance on these category of students. However, 7 students were predicted to have high risk; this category of students deserves special attention so that they can cope well with their studies. Generally, cases with values above 0.5 have satisfactory academic achievement, while cases with values less than 0.5 needs to sit up and make extra efforts to meet the challenges ahead.

VI. CONCLUSION

This research adds to the rationale for having prior knowledge about the academic achievement of all the newly admitted and registered students, at the earliest possible time of their studentship, with a view to determining their strengths and weaknesses.The researchers modelled the transformed input predictive variables using the approach of fuzzy logic. The various methods used to predict student's performance were discussed; the risk status of students of Computer Science department which comprised of 37 records were predicted in this research, the researchers would extend the technique to cover many departments across faculties in subsequent research. The technique of fuzzy logic applied in this research shows its capability of handling uncertainty.The results segmented the students according to their risk status, the model can be applied to predict the academic performance of all applicants seeking admission to Nigerian institutions of higher learning and the technique used can be generalized to make similar prediction in any institution outside Nigeria. Exploring students' achievement at the early stage of their studies would help the teacher to pay special attention to students predicted to have high risk of failure and render needed assistance to them when it matters most.

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