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Exploiting the Core Academic Performance Prediction Parameters Using a Neuro-Fuzzy Model

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Abstract: *This work developed a Neuro-Fuzzy model as an intelligent computational framework to provide decision support for the admission of candidates into Higher Institutions. The traditional admission process is based on Unified Tertiary Matriculation Examination (UTME) and Post- Unified Tertiary Matriculation Examination (Post-UTME) scores, so long as the O-Level requirements are satisfied. This method has proven to have limitations. In this work, a five layer Adaptive Neuro-fuzzy Inference System (ANFIS) is modeled using a fuzzy logic input decision variables, taking into consideration the aggregate previous academic performances of the candidate and other related parameters that can influence academic performance. Historical records of students' academic performances are used to build the fuzzy logic decision tree from which the initial fuzzy logic rules are extracted. The MATLAB NeuroFuzzy Designer is used for the modeling and training of the ANFIS model. Validation of the accuracy of the prediction using the affected student's year 1, 2 , 3, 4 and 5 CGPAs, give the coefficients of multi determination* R^2 *to be approximately 0.96, 0.97 , 0.99, 0.98 and 0.96 respectively. These results show very high degree (97.2%) of accuracy, between the predicted and actual performance. These findings show that the developed model can be relied upon to make decisions on the admission of candidates into HAILs in any country of the world.*

Keywords: *Decision Support System, Fuzzy Logic, Neural Network, HAIL, Admission, Prediction, etc*

I. INTRODUCTION

Higher Institutes of Learning face the challenge of selecting and admitting those who can perform well in undergraduate years. Many institutions embrace the traditional admission system which uses a set of national qualifying and University specific examination outcomes for making admission decisions. The traditional admission process is based only on UTME and Post-UTME scores, given that the candidate has credited the required five subjects in the ordinary level examinations. This traditional admission process has not been yielding the best crop of students in terms of academic performance. This is because the circumstances of writing the national qualifying examinations are often flawed and fraught with malpractices from undeserving students who can afford to cheat. This is especially the case nowadays where Organized UTME/WAEC/NECO/GCE Syndicates that promise and "ensure" that their ‘‘customers’’ pass their national examinations at or above the required HAIL admission performance level in one sitting. The traditional admission paradigm focuses on assessing only the end product (examination scores and grades), neglecting the specific knowledge and academic abilities which are part and parcel of the learning outcomes of the candidates' previous education. Therefore, the admission approaches in Nigeria should go beyond simply matching test scores and admission requirements. Literature suggests that candidates' historical academic and personal data, qualities, skills, attributes and other relevant factors are predictive of their future academic performance in tertiary education (Adeyemi, 2010). There is therefore the need to develop an alternative admission process that would need to be performance-based and facilitate the assessment of admitting candidates from a holistic perspective.

The integrity of admissions processes at Higher Academic Institution of Learning (HAIL) depends upon the unbiased determination of the appropriate merits of each prospective student. HAIL is often the focus of negative media attention due to reports of undue influence in admission decisions where due process is said not to be followed. That is, shadow admissions process exists, catering for applicants who were supported by public officials, University Trustees, donors, and other prominent individuals. The damage done by the existence of this hidden, yet institutionalized, admission process tends to undermine public confidence in the HAIL and their leadership. There is suspicion of a double standard that favours well-connected applicants. The work under this study will ensure admission decision of prospective students in a fair and consistent manner. This will help maintain public trust that student admissions are centred on merit. This alternative approach will facilitate easier and faster admission processing that will be possible to process large volumes of admission candidates' data within a very short time. Furthermore, HAIL will have the benefit of admitting motivated and high performing students as they will have had a better chance of selecting applicants into courses of studies not by coincidental high UTME or Post-UTME scores but based on their cumulative academic records and other background and personal quality factors.

II. LITERATURE REVIEW

Research has been done in the use of neural networks for pattern recognition or classification. Many studies have been conducted on the application of artificial neural networks in computer security, detection of computer intrusion and detection of computer viruses, image detection, and fingerprint recognition. However, hardly any research exists in the area of student selection for University admission. Research activities in neural classification have established that neural network is a promising alternative to various conventional classification methods (Zhang, 2000). On the other hand, current rule-based systems, expert systems, are weak in their ability to deal with the uncertainties inherent in real-world information and lack the ability to generalize to novel problems (Goodman, Higgins & Miller, 1992).

While there is an increasing need for a more accurate system capable of identifying the academic qualities for students to join suitable University courses, there is currently no applied alternative to rule-based systems. Rule-based systems can be relatively effective if the exact academic qualities of students are known. However, these qualities of students are ever changing depending on the quality of examinations, marking, teaching and other socio economic factors. Rule-based systems cannot accurately identify a variety of students who qualify to be selected for certain University courses as a large group of students attain a minimum grade to join Universities. The qualities of examinations and teaching standards are also changing constantly. As a result, many students are misplaced or rejected.

The quality of examinations, teaching standards, and curriculum may affect the academic qualities of a student required for a particular course. Therefore, the process of selecting students requires a flexible system that is capable of analyzing vast volumes of student requirements in a less structured manner than the rule-based system. Artificial neural network system could potentially address many of the problems experienced with rule-based systems more effectively. The research study on Predicting Students' Academic Performance using Artificial Neural Network (with an Engineering Course a Case Study) by Oladokun, Adebanjo and Charles-Owaba (2008) used an ANN model for predicting the likely performance of a candidate being considered for admission into the university. The authors identified the various factors that may influence the performance of a student as including ordinary level subjects' scores and subjects' combination, matriculation examination scores, age on admission, parental background, types and location of secondary school attended and gender, among others. These variables were the inputs to the ANN using Multilayer Perceptron Topology. Data spanning five generations of graduates from an Engineering Faculty was used for training purposes. Test data evaluation showed that the ANN model was able to correctly predict the performance of more than 70% of prospective students.

Scholastic Assessment Test (SAT) is a standardized test widely used for college admissions in the United States. Wilson (1999) reviewed studies predicting College (University) Cumulative Grade Point Averages (CGPA) and graduation. Burton and Ramist (2001) reviewed studies of the validity of the SAT and high school record as predictors of such long-term measures of success in college as cumulative grade Point Average (CGPA), graduation, leadership, and post-college income. Both reviews found that SAT scores made a substantial contribution to predicting cumulative GPAs, and that the combination of SAT scores and high school records provided better predictions than either grades or test scores alone. The studies are typically based on a statistical correlation between admission credentials ("predictors") and available measures of success in the institution ("criteria").

De Winter and Dodou (2011) investigated the extent to which high school exam scores predict first-year Grade Point Averages (GPA) and completion of Bachelor of Science (B.Sc.) programs at a Dutch technical University. It was hypothesized that, of the exam scores, those for Mathematics and physics would be the strongest predictors of academic performance. Factor analysis of high school exam scores was performed for a group of 1,050 students. Regression analysis of the extracted factors was conducted to predict first-year GPA and B.Sc. completion. The results showed that the Natural Sciences and Mathematics factor (loading variables: Physics, Chemistry, and Mathematics) was the strongest predictor of first-year GPA and B.Sc. completion, the Liberal Arts factor was a weak predictor, and the Languages factor had no significant predictive value. Differences were identified across the B.Sc. programs, with programs that relied strongly on Natural Sciences and Mathematics enrolling better-performing students. Arora and Saini (2013) presented a Neural Network model for modelling academic profile of students. The proposed model allows prediction of students' academic performance based on some of their qualitative observations. Classifying students' academic performance using arithmetical and statistical techniques may not necessarily offer the best way to evaluate human acquisition of knowledge and skills, but a hybridized fuzzy neural network model successfully handles reasoning with imprecise information, and enables representation of student modelling in the linguistic form - the same way the human teachers do. The model is designed, developed and tested in MATLAB and JAVA which considers factors like age, gender, education, past performance, work status, study environment etc. for performance prediction of students. A Fuzzy Probabilistic Neural Network model has been proposed which enables the design of an easy-to-use, personalized student performance prediction component. The results of experiments show that the model outperforms traditional back-propagation neural networks as well as statistical models. It is also found to be a useful tool in predicting the performance of students belonging to any stream. The model may provide dual advantage to the educational institutions; first by helping teachers to amend their teaching methodology based on the level of students thereby improving students' performances and secondly classifying the likely successful and unsuccessful students.

Garton, Dyer, and King (2000) research was conducted with College freshmen to assess the effectiveness of University admission variables and student learning style in predicting students' academic performance and retention. Learners preferring a field-independent and field-neutral learning style exhibited greater academic performance than their field-dependent peers during the first year of college as evidenced by GPA. The best predictors of academic performance during the first year of college were high school GPA and ACT score. The predictors are the modes of entry and qualifications for admission into the University while the criterion is the Final Cumulative Grade Point Average (CGPA) at the end of University education. The sample for the study consisted of four hundred and sixty three (463) faculty of Business students who graduated in years 2007, 2008 and 2009. The stepwise regression was used for data analysis. The major findings of the study are that in general, ordinary level Mathematics and advanced level Accounts are predictors of academic success, and that the Cumulative Grade Point Average (CGPA) at the end of pre-University examination predicts academic success of the pre-University entrants.

The criterion most frequently used in these studies designed to assess the predictive validity of measures used in College admission has been the freshman-year GPA. It is not self evident that the first-year GPA provides either a sufficient or a representative sample of a student's academic performance. Curtis, Lind, Brear and Finzen (2007) compared admissions criteria as predictors of Dental school performance in under achieving and normally tracking Dental students. Underachieving dental students were identified by selecting ten students with the lowest class grade point average following the first year of Dental school from five classes, resulting in a pool of fifty students. Normally tracking students served as a control and were randomly selected from students who had completed their first year of dental school not in the under achieving group. Admission measures of college GPA, Science Grade Point Average (SGPA), Academic Average (AA), Perceptual Ability Test (PAT), college rigor, and academic load in College were evaluated with descriptive statistics, correlation, and regression analysis with first-year and graduating GPA as the dependent variables. Admissions criteria were generally weak predictors of first-year and graduating GPA. However, first-year Dental School GPA was a strong predictor (R2=0.77) of graduating GPA for normally tracking students and a moderate predictor (R2=0.58) for underachieving students. Students who completed the first year of Dental school having a low GPA tended to graduate with a low GPA.

Conard (2006) investigated the incremental validity of Big Five personality traits (openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism) for predicting academic criteria (College GPA, course performance) while controlling for academic ability (Scholastic Aptitude Test (SAT)). Results showed that conscientiousness incrementally predicted each criterion over SAT. Results also showed that behavior (attendance) incrementally predicted GPA and course performance and it mediated the relationship between conscientiousness and both academic criteria. Personality measures are promising predictors of academic outcomes and they may have usefulness in admissions and student development.

Cullen, Sackett, and Lievens (2006) examined the coach ability of two situational judgment tests including College Student Questionnaire (CSQ) for consideration as selection instruments in the College admission process. Their results indicated that the CSQ test was susceptible to coaching and that the scoring format of the test could be easily exploited, such that candidates could increase their scores simply by avoiding extreme responses on that test. The study results as a whole sounded a note of caution for the potential use of test in the college admission process.

The study by Cunningham (1982) related junior-level grade point average, student birth year, assertion inventory scores, previous organization leadership and membership roles, volunteer experience, and work experience, to later performance ratings in an undergraduate fieldwork program for 83 Bachelor of Social Work (BSW) students. The performance ratings were done by University faculty liaisons after input from the agency supervisor. The multiple regression analysis indicated that only grade point average and age were significant success predictors. Younger students with higher grade points performed better in the fieldwork program.

Veloski, Callahan, Gang, Hojat, and Nash's (2000) study simultaneously evaluated the relative importance of Medical College Admissions Test (MCAT) scores, undergraduate GPAs, age, race, and sex in predicting students' performances on the sequence of three licensing examinations over a period of three decades. The researchers used multivariate linear regression model for the evaluation. The results of the study showed that MCAT scores were consistently more valuable than were undergraduate GPAs as predictors of performance on licensing examinations, supporting their continued use in selection decisions. These relationships are stable across three decades and apply to the three examinations. Verbal scores tended to be better indicators of performances in the clinical and postgraduate tests.

Hoefer and Gould (2000) research was concerned with quantitative measures currently used or having the potential to be used in the student admission processes for graduate schools of business to produce the best academic performance by admitted students. Methods used to assess the importance of various admission criteria were classified into traditional (linear and nonlinear regression methods) and nontraditional (neural network) multivariate data analysis techniques. In the results for comparing methods, one familiar test, measuring the residual error on a common data set, suggests that neural networks may provide a better predictive model of admitted students' academic performance than traditional quantitative methods of data analysis.

Fang, Ko, Chien, and Yu (2013) examined whether students admitted using different admission programs gave different performances. The study employed various assessment tools, including student opinion feedback, multi‐source feedback (MSF), course grades, and examination results. The MSF contained self ‐assessment scale, peer assessment scale, staff assessment scale, visiting staff assessment scale, and Head assessment scale. In the subscales, the Cronbach's alpha were higher than 0.90, indicating good reliability. Their results indicated that the performance of students who were admitted through the recommendations of their schools exceeded that of students who were enrolled through the National College University Entrance Examination (NCUEE).

Woosley and Shepler (2011) study was to determine if College of business admission criteria and other variables predicted undergraduate College of business student graduation. The specific variables examined in the study included gender, race/ethnicity, math academic aptitude score, verbal academic aptitude score, College of business accounting GPA, college of business computer proficiency GPA, College of business economics GPA, College of business statistics GPA, required English GPA, and required math GPA. Results of the logistic regression indicate the model was statistically significant. Specifically, the variable college of business statistics GPA was positively associated with high probabilities of graduation. Further, about 87% students meeting the college of business admission criteria who began their studies in the fall of 2000 had graduated by July of 2005. Specifically, about 87% of the students who completed the requirements for admission into the College of business actually graduated. Second, the variable, College of business statistics GPA, appears to be the most influential variable in predicting college of business student graduation at this institution.

Naik and Ragothaman (2004**)** predicted MBA student performance for admission decisions. Their work evaluated the ability of three different models--neural networks, logit, and probit to predict MBA student performance in graduate programs. The neural network technique was used to classify applicants into successful and marginal student pools based on undergraduate GPA, GMAT scores, undergraduate major, age and other relevant data. The results of this study show that the neural network model performs as well as the statistical models and is a useful tool in predicting MBA student performance. O'Connor and Pauninem (2007) reviewed the recent empirical literature on the relations between the Big Five personality dimensions and post-secondary academic achievement, and found some consistent results. A meta-analysis showed Conscientiousness, in particular, to be most strongly and consistently associated with academic success. In addition, Openness to Experience was sometimes positively associated with scholastic achievement, whereas Extraversion was sometimes negatively related to the same criterion, although the empirical evidence regarding these latter two dimensions was somewhat mixed. Importantly, the literature indicates that the narrow personality traits or facets presumed to underlie the broad Big Five personality factors are generally stronger predictors of academic performance than are the Big Five personality factors themselves. Furthermore, personality predictors can account for variance in academic performance beyond that accounted for by measures of cognitive ability. A template for future research on this topic is proposed, which aims to improve the prediction of scholastic achievement by overcoming identifiable and easily correctable limitations of past studies. Iuliana Ianus (2001) in his report presents a study to improve prediction of freshman GPA based on College admission data to better inform the decision as to who to admit to Carnegie Mellon University (CMU). This analysis assessed the utility of the non-academic data to end a better algorithm for making this prediction. Data for two consecutive entering classes at CMU were used. Both classical and Bayesian approaches were performed here. The classical methods allowed us to better understand the previous criterion of acceptance and to investigate the significance of a difference between students who were admitted and enrolled and the students who were admitted and did not come to CMU. A Bayesian predictive approach was used to identify the cutoff based on admission data for the predictive probability that a students' first semester GPA is greater than 2.0.

Al-Alwan (2009) assessed the correlation between admission criteria to Health Science Colleges, namely, final high school grade and Saudi National Aptitude and Achievement exams, and early academic performance in these Colleges. The study included 91 male students studying in the two-year pre-professional program at the King Saud bin Abdulaziz University for Health Sciences (KSAU-HS), Riyadh, Saudi Arabia. Records of these students were used to extract relevant information and their academic performance (based on the grade point average achieved at the end of the first semester of the pre-professional program), which were analytically studied. Pearson correlation coefficient was used to assess the associations between the different scores. SPSS statistical program (version 12.0) was used for data analyses. A strong correlation was found between the academic performance and the Achievement Exam, Aptitude Exam and high school final grade, with Pearson Correlation Coefficients of 0.96, 0.93, 0.87, respectively. The Saudi National Achievement Exam showed the most significant correlation. Results indicate that academic performance showed good correlation with the admission criteria used, namely final high school grade, Saudi National Aptitude and Achievement Exams.

Häkkinen (2004) examined the factors that predict academic performance at university and compared the predictive values of subject-related entrance exams and indicators of past school performance. The results show that in the fields of engineering and social sciences entrance exams predict both graduation and the number of study credits better than past performance. In education, past school performance is a better predictor of graduation. Changing the admission rule to school grades would affect the average student performance negatively in engineering and social sciences but positively in education. Using only entrance exams would not significantly change the average performance in any field.

In summary, it is therefore noted that different analysis has been done on students' results repository, which qualifies them for admission into universities but the aggregate in all their various examination results that qualifies them for admission in comparison with their academic history and family background has never been analyzed for hidden but important patterns. Analyzing and searching for these patterns with respect to their performance in the first academic year could be of a great importance to academic planners in enhancing their decision making process and improving student performance. In order to bridge this gap, this research presents an analysis of aggregate of Past Academic records, Family Background, UME, PUME, O'level and first year CGPA in predicting the best pattern that mostly occur in the repository of students records, using Artificial Neural Network algorithm.

III. METHODOLOGY

The methodology used for the development of the Neuro-Fuzzy network entails modeling & design, training & validation of the network. Training is required for the network to make adjustments to the weights or firing strengths of the neurons in the network. Data is required for the training and validation of the Neuro-Fuzzy network. In this work historic data on academic performance variables for 500 students are collected. The online data capture & management program module (refer to Fig. 3.1) specially developed as part of the proposed students admission decision support framework is used to collect the required data.

The data collected has among others the core academic assessment decision variables:

- Primary School Average
- Secondary School Aggregate Performance
- O'Level Scores in Selected Subjects
- Post UTME subjects

These fields in the dataset extracted make up the fuzzy linguistic variables in the modeling of the neuro-fuzzy network. The neuro-fuzzy network is modeled based on the Adaptive Neuro-fuzzy Inference System (ANFIS) architecture. For the modeling and design of the network, a dataset of 20 records extracted from the historic records is used to build a fuzzy decision tree, using the fuzzy concepts learning system (FCLS) algorithm.

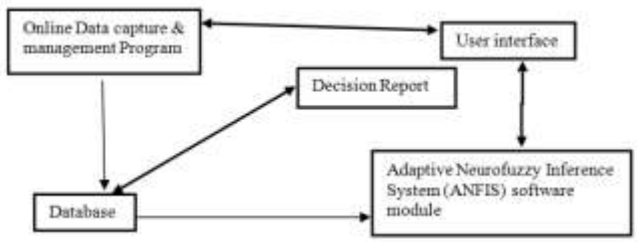


Fig. 1: Block diagram of the intelligent framework to provide decision support for the admission of students into HAILs.

The neuro-fuzzy network software is created with MATLAB. The MATLAB fuzzy logic toolbox and neural network toolboxes are used in the creation, training and validation of the neuro-fuzzy model. The tools used in the creation and deployment of the online data capture & management program are phpMyAdmin, MySQL database, PHP, HTML authoring tools, Microsoft ASP.NET web server backend technology and JQuery language. The core of the methodology is the use of the historic academic data collected with the neuro-fuzzy network software to predict the future academic performances of the candidates being processed for admission into HAILs. This prediction would be validated against the actual performances of the students using their year 1, 2, 3,4 & 5 cumulative grade point averages (CGPA).

Simulation is used to test and validate the performance of the proposed decision support system. The mathematical method used for the evaluation of the accuracy of the predictions entails the use of multi regression analysis. The online data capture and management program is designed, developed and deployed to run in backend web server. It is equipped with the program logic to capture data on students' academic performance variables and to maintain the data on a back end database server.

The user interface program enables a user to interact with the framework. Through the user interface, a user can supply data to the online data capture program which formats it and stores it in the database (encoded in a format for the use of the ANFIS component). A user can use the user interface to initiate the invocation of the ANFIS program for training and predictive processing. The command vector to the ANFIS component includes the information on the segments of the records to fetch from the database as the dataset for training and for prediction processing. The ANFIS program upon invocation can connect to the database and fetch the historic data specified in the user query, in order to initiate execution. After processing execution, the result set is stored in the database in serialized and tagged format. The user can obtain the result via the decision reporting component. This component has the code logic to format the predicted output in the format that enables the admission processing personnel to ascertain the suitability of the particular candidate for admission placement.

IV. SYSTEM DESIGN

First FCLS (Fuzzy Concepts Learning System) is used to build a fuzzy decision tree using a dataset of 20 records extracted from candidates' historic academic records. Based on the constructed fuzzy decision tree, the initial rules used by the neuro-fuzzy network is modeled on the basis of the ANFIS (Adaptive Neuro-Fuzzy Inference System) architecture. To apply the FCLS to build the fuzzy decision tree and subsequently extracting the initial fuzzy linguistic rules, the dataset given in table 1 is used. The dataset is extracted from the academic historical records of students as supplied by the students in response to the questionnaire used in this work as data collection instrument. The dataset has the following fields:

- Primary School Average(PSA)
- Secondary School Aggregate Performance(SSAP)
- O'Level Scores in Selected Subjects(OSS)
- UTME Scores in Selected Subjects(UMESS)
- Predicted Academic Performance(PAP)

These fields constitutes the decision variable for the prediction of future academic performance of the students for admission into HAILs. In this design these decision variables make up the fuzzy linguistic variable. A dataset is used to specify the initial rules for the decision making. The neural network module is used to tune the initial fuzzy membership functions to make weight adjustment and to derive new rules. The membership curve for PAP is in Fig. 2. The membership function quantitatively defines the linguistic rules. The neural network learning ability is used to automate this process. The linguistic rules are linked with neural network to produce the decision inference for the selection of suitable students for placement into HAILs. By extracting the fuzzy logic rules and optimizing the membership function through neural network connective weights, the design establishes a neuro-fuzzy model. The neuro-fuzzy model improves the prediction of the candidates' future academic performance to better support the decision for admitting students into HAILs.

Table 1: Dataset used for the FCLS algorithm

S/N	PSA	SSAP	OSS	UMESS	PUTME_Avg	PAP
1	76	89	72	87	78	80.4
2	42	47	59	45	49	48.4
3	58	60	41	48	52	51.8
4	36	28	33	70	54	44.2
5	78	58	57	66	58	63.4
6	22	18	24	61	47	34.4
7	60	79	76	82	83	76
8	64	40	36	31	28	39.8
9	32	55	42	32	30	38.2
10	56	48	58	56	45	52.6
11	32	35	18	35	32	30.4
12	46	56	58	42	49	50.2
13	20	36	28	25	20	25.8
14	31	34	45	39	42	38.2
15	74	72	88	76	83	78.6
16	14	26	20	56	47	32.6
17	52	72	63	56	49	58.4
18	48	67	82	56	54	61.4
19	70	17	74	40	36	47.4
20	78	89	82	78	87	82.8

V. FUZZIFICATION OF THE DATA SET

This is the fuzzification of the dataset of table 1. From 1, it can be seen that the attribute PAP is determined by the attributes PSA, SSAP, OSS, UMESS, PUTME_Avg. Hence

$Z = \{PSA, SSAP, OSS, UMESS, PUTME\_Avg\}$
Z = PAP.
Where attributes PSA, SSAP, OSS, UMESS, PUTME_Avg are called **antecedent attributes** and the attributes PAP is called **the consequent attribute.**
The domains of the attributes PAP, PSA, SSAP,UMESS and PUTME_Avg are from 0-100%. The fuzzy domain of these attributes is **{LOW(L),MODERATE(M),HIGH(H)}.**

Using MATLAB Fuzzy Toolbox program, the membership functions of this parameter is shown in Fig. 2.

Implementing STEP 1 of the FCLS Algorithm:
Using the values in the dataset of table 1 and the membership function curves of Figs. 2 the results of the fuzzification of the relation in table 1 is the fuzzy relation.

Where : H = HIGH ; M =MODERATE; L = LOW.
Implementing STEP 2:
Select an attribute among the set
$S = \{PSA, SSAP, OSS, UMESS, PUTME_{Avg}\}$of antecedent attributes that has the smallest FA(fuzziness).
Based on equation (1), the fuzziness of each attribute in the set S is computed as follows:

$$FA(PSA) = [(1-0.48) + (1-0.54) + (1-0.64) + (1-0.15) + (1-0.50) + (1-0.4) + (1-0.62) + (1-0.52) + (1-0.2) + (1-0.62) + (1-0.2) + (1-0.78) + (1-0.5) + (1-0.21) + (1-0.46) + (1-0.67) + (1-0.92) + (1-0.58) + (1-0.2) + (1-0.50)]/20$$
$$= \frac{10.38}{20}$$
$$= 0.59$$

$$FA(SSAP) = [(1-0.54)+(1-0.58)+(1-0.5)+(1-0.22)+(1-0.64)+(1-0.52)+(1-0.26) + (1-0.7)+(1-0.72)+(1-0.58)+(1-0.12)+(1-0.62)+(1-0.15) + (1-0.14)+(1-0.25)+(1-0.23)+(1-0.25)+(1-0.48)+(1-0.57) + (1-0.58)]/20$$

$$= \frac{11}{20}$$
$$= 0.5675$$

$$FA(OSS) = [(1-0.25)+(1-0.62)+(1-0.36)+(1-0.18)+(1-0.68)+(1-0.26)+(1-0.48) + (1-0.15)+(1-0.54)+(1-0.64)+(1-0.52)+(1-0.64)+(1-0.22) + (1-0.78)+(1-0.56)+(1-0.5)+(1-0.52)+(1-0.22)+(1-0.46) + (1-0.22)]/20$$

$$= \frac{11.23}{20}$$
$$= 0.5613$$

$$FA(UMESS) = [(1-0.52)+(1-0.75)+(1-0.58)+(1-0.2)+(1-0.50)+(1-0.6)+(1-0.22) + (1-0.21)+(1-0.2)+(1-0.62)+(1-0.12)+(1-0.54)+(1-0.24) + (1-0.1)+(1-0.48)+(1-0.62)+(1-0.62)+(1-0.62)+(1-0.7) + (1-0.50)]/20$$

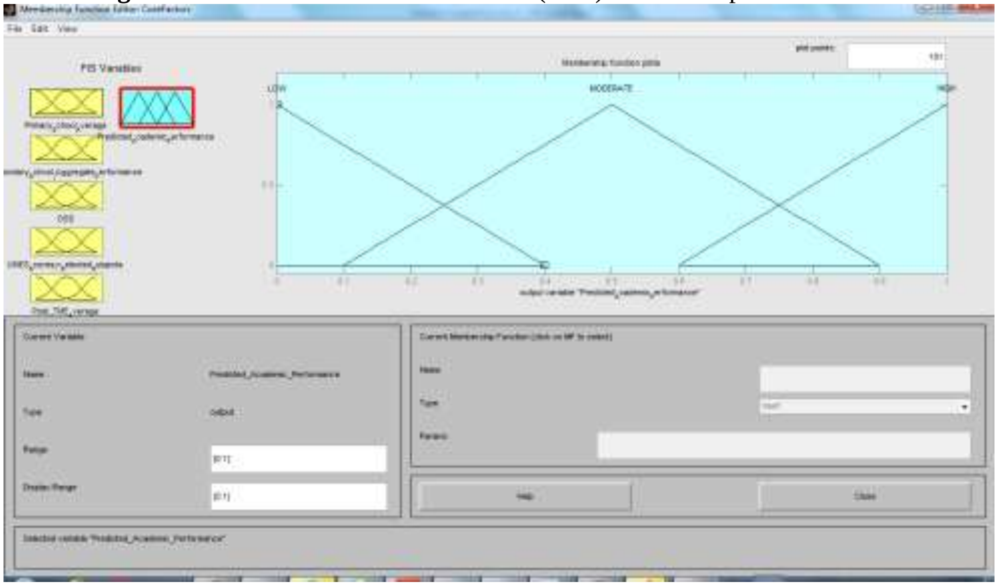
$$= \frac{11.06}{20}$$
$$= 0.553$$

$$FA(PUTME\_Avg) = [(1-0.5)+(1-0.89)+(1-0.92)+(1-0.74)+(1-0.64)+(1-0.58)+(1-0.2) + (1-0.22)+(1-0.18)+(1-0.75)+(1-0.2)+(1-0.89)+(1-0.5) + (1-0.54)+(1-0.28)+(1-0.58)+(1-0.89)+(1-0.74)+(1-0.15) + (1-0.54)]/20$$

$$= \frac{9.07}{20}$$
$$= 0.4535$$

From the computation the attribute that has the smallest fuzziness (FA) is $PUTME\_Avg$, hence this attribute is taken as the decision node.(i.e the root node)

Fig. 2: Predicted Academic Performance (PAP) membership function curve



VI. DEVELOPMENT OF THE NEURO-FUZZY NETWORK MODEL FOR DECISION SUPPORT FOR THE ADMISSION OF STUDENTS INTO HAILS

Two Neuro-fuzzy models are developed. One of the models can be utilized entirely on its own to do the job. This model takes the core academic variables as inputs. It uses as inputs the following variables: PSA, SSAP, OSS, UMESS, and PUTME_Avg to output the PAP. However, the prediction would be richer if a second neuro-fuzzy model which takes as input other subsidiary academic performance influence variables is integrated with the first core neuro-fuzzy model. The second neuro-fuzzy model takes the following subsidiary academic performance influence variables as inputs:

- Parents Education Status(PES)
- Family Income(FI)
- Zonal Location of Secondary School(ZLS)
- Type of Secondary School Attended(TSS)

Despite the usefulness of the second neuro-fuzzy model, the admission decision can still be done with great accuracy based only on the first neuro-fuzzy model. In a combination of the first and second models, the effect of the second model can still be held constant by feeding in (in-putting) unit values. Hereafter the first neuro-fuzzy model is referred to as the Core Academic Performance Prediction Neuro-fuzzy model, while the second one is referred to as the subsidiary academic performance prediction neuro-fuzzy model.

VII. THE CORE ACADEMIC PERFORMANCE PREDICTION NEURO-FUZZY MODEL

The model uses: PSA, SSAP, OSS, UMESS and PUTME_Avg as inputs for the prediction of future academic performance (PAP) of any target candidate for HAIL placement. For the fuzzification of the model's input variables, the fuzzy sets used are {LOW, MODERATE, HIGH}. The associated fuzzy inference rules are dynamically generated by the model. This is done by the adaptation of the initial fuzzy rules as specified earlier. The five layers, feed forward neuro-fuzzy model for the prediction of candidates' academic performance is shown in Fig. 3. The output layer 5 is the Predicted Academic Performance (PAP).

The network in Fig. 3 is constructed in AutoCAD using the following principles:

1. The number of nodes in layer 1 (the input layer) is equal to the number of inputs (PSA, SSAP, OSS, UMESS, PUTME_Avg). Each node in this layer is labeled $\prod$.
2. The number of nodes in layer 2 (the fuzzification layer) is equal to the number of fuzzy sets. In this design each of the five inputs has a scale of three fuzzy set {LOW, MODERATE, HIGH} of different membership degrees.
3. The number of nodes in layer 3 (the rule layer) is equal to the number of rules. Each node in this layer is labeled N.
4. The number of nodes in layer 4 (the adaptive node with the consequent parameter) is same as in layer 3.
5. Layer 5 is a single node layer that computes the overall output as the summation of all incoming signals. The single fixed node of this layer is labeled $\sum$.

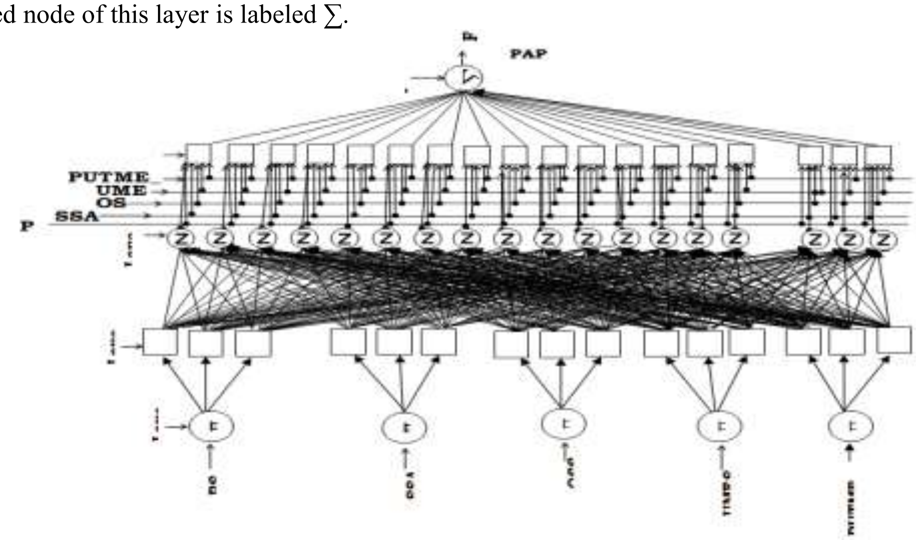


Fig. 3: Neuro-fuzzy model for predicting academic performance of candidates for admission into HAILs using core academic performance variable as inputs

The number of nodes in layer 1 and 2 is equal to the number of input variables, the number of nodes in layers 3 and 4 is equal to the number of dynamic fuzzy rules, being equal to 2^{n-1} where n is the number of the variables. For the description of the model of Fig. 3.10, O_1, i is used to denote the output values of node i in layer 1. The single node in this layer is a fixed node labeled $\sum$, which computes the overall output as the summation of all incoming signals:

$$Overall\ output = O_{5i} = \sum_i w_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \qquad \text{.................. (1)}$$

The developed neuro-fuzzy forecast model is a self-organized, two-phase learning process with phase one to locate the initial membership function and phase two to fire the fuzzy rules. In phase 1, the center and the width of the initial membership function are determined by the feature-map algorithm (Burkhardt and Bonissone, 1992): The above learning algorithm shows the computational procedures in the design of adaptive neuro-fuzzy model. After training and validation by another set of input and output, the neuro-fuzzy model can be applied to Predicting the academic performance of candidates as a decision support tool to help determine the suitability of candidates for placements in HAILs.

VIII. SUBSIDIARY ACADEMIC PERFORMANCE PREDICTION NEURO-FUZZY MODEL

The five layers, feed forward neuro-fuzzy model for the prediction of candidate's academic performance using the subsidiary influence variables is shown in fig. 4. The output, layer 5 is the subsidiary Predicted Academic Performance (SUB_PAP).

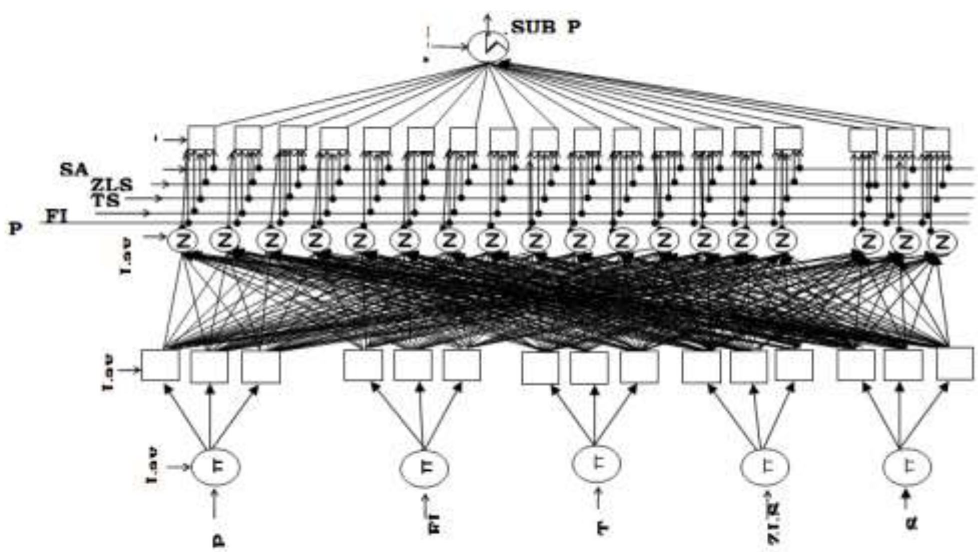


Fig. 4: Neuro-fuzzy model for predicting academic performance of candidates for admission into HAILs using subsidiary academic performance influence variable as inputs

IX. TRAINING THE ANFIS PREDICTION MODEL

The MATLAB **Neuro-Fuzzy Designer** is used to train the neuro-fuzzy prediction model. The main computing occurs on the training blocks. Here the hybrid algorithm is used. For the training the error tolerance is set to 0.01. Though the default value for the epoch MATLAB Neuro-fuzzy Designer is set to 3, for the training carried out in this work it is set to 100. Epoch means number of iteration. This is a parameter in the training of intelligent models like Neural networks, neuro-fuzzy networks, Bayesian networks etc. It is not unusual to have hundreds or even thousands of iterations, however in this work 100 is used. A database query is issued to extract the training data from the database attached to the online data management program. SQL sorting command phrase is used to limit the data to the dataset used for the training of the prediction model. The query returned data is converted to CSV file and exported to the Neuro-fuzzy prediction program written. The MATLAB program reads the CSV file and loads it into the MATLAB workspace in matrix form. Where the first column is the averaging of the PSA, SSAP, OSS, UMESS &PUTME_Avg and the second column is the students' CGPA. During the training, after loading the extracted dataset, MATLAB neuro-fuzzy Designer loads the initial ANFIS structure, as modeled in Fig. 3 and Fig. 4.

X. RESULT AND DISCUSSION

From the block diagram given in Fig. 1, the online data management program is used to obtain data on the parameters used for the Neuro-fuzzy academic performance prediction model. The online data management component collects data on the core academic variables. The values entered for PSA, SSAP, OSS, UMESS, PUTME_Avg, PES, FI, ZLS and TSS are entered and stored in a database. A database query is used to extract the data. The data is converted to Comma Separated Values (CSV) file and exported into the Neuro-fuzzy based prediction program written in MATLAB. This MATALAB program reads the CSV file and loads it into the MATLAB workspace as matrices and vectors of values. Figs. 5 gives screen shots from the online data management program, showing the parental factors, tabulation of the students' data, past academic records with admission examination score and the admission decision page respectively.

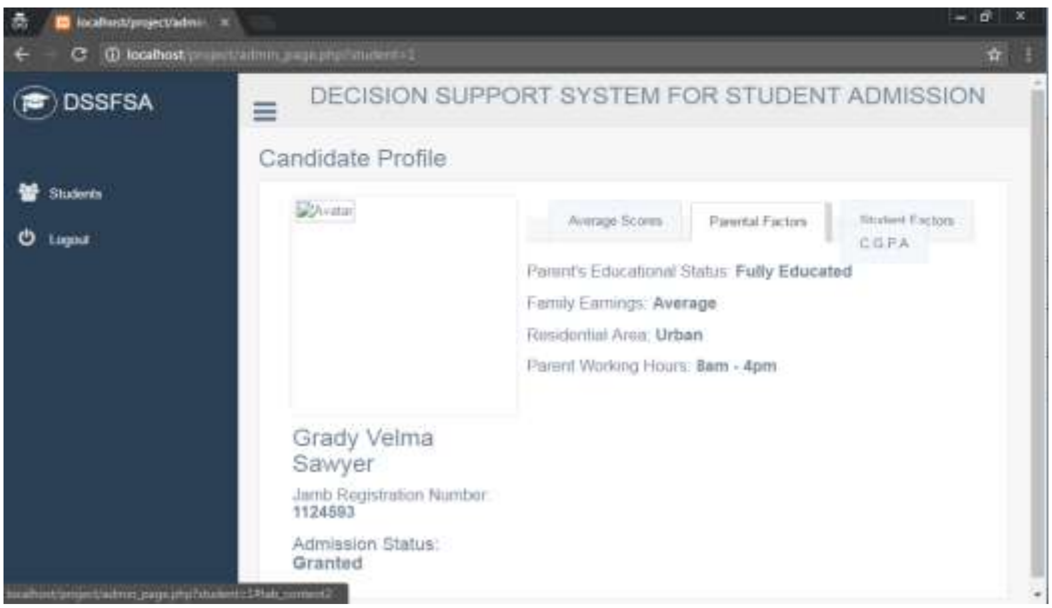


Fig. 5.: Screen shot showing student's online admission decision page

XI. TESTING AND VALIDATING THE NEURO-FUZZY PREDICTION MODEL

The data is sorted on the CGPA using database bordering query. It is necessary to sort the data in order to graphically represent the trend of the data. The data is sorted in ascending order of the predicted academic performance and the corresponding actual academic performance. The academic performance is in the data structure, range and format of CGPAs. The data is loaded into the MATLAB workspace using the technique as described previously. The predicted academic performance of the students sorted in ascending order is given in table 4. The data is sorted using the database Order by clause in the SQL issued to the database. The returned dataset is ordered on the predicted CGPA. Fig.4.5 gives the graphical representation of the statistical distribution of the predicted academic performance (i.e. the predicted CGPAs). Fig. 5 indicates that the model predicted that around 70% of the students will perform below the equivalent of CGPA of 2.5 (which is low), hence are not deemed suitable to be given admissions into HAILs. Referring to table 4.1, the students that have been predicted to perform below this CGPA can be clearly identified.

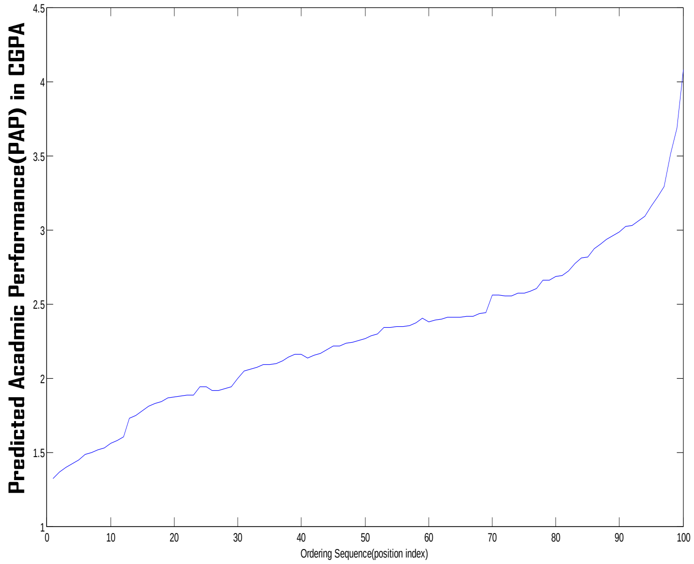


Fig. 6: Statistical distribution of the Neuro-Fuzzy model Predicted Academic Performance (PAP) after records ordering

XII. EVALUATION OF THE ACCURACY OF THE PREDICTION

The degree of deviation of the performance prediction from that of the actual academic performance is used to evaluate the accuracy of the developed prediction model. Accuracy requires that the predicted academic performance have to be correlated with the actual academic performance. The computational technique of regression is used to find the correlation (or the variance) between the predicted data set and the observed data set for the student's academic performance. Hence the measure used to evaluate the accuracy of the prediction model is the coefficient of multiple determinations (R^2). This statistical coefficient measures the discrepancy (i.e. variation) that exsit between the points on the predicted graphical distribution and points on the actual distribution. The value of R^2 is between 1 and 0. $R^2 = 1$ means that a very close relationship exists between the prediction and the actual (observed) data set (the value of 1 means a perfect forecast). The contrast, $R^2 = 0$ means no correlation exists between the predicted and the actual data set (very poor prediction).

For the calculation laid out in table 4.2, Let actual academic performance = $\boldsymbol{y}$; Let the predicted academic performance = $\hat{\boldsymbol{y}}$; let the mean of the sampled actual academic performance = $\bar{\boldsymbol{y}}$

$\bar{y} = \frac{\Sigma y}{100} = \frac{235.25}{100} = 2.3525$ ………………………………………4.1

The coefficient of multiple determination is given by R^2

$R^2 = \frac{\Sigma(y-\bar{y})^2 - \Sigma(y-\hat{y})^2}{\Sigma(y-\bar{y})^2}$…………………………………………………………..4.2

Hence R^2 for the prediction of academic performance and using year 1 data is

$= \frac{30.4245 - 1.1461}{30.4245} = 0.96233$

. From the computation, the coefficient of multiple determination

$R^2 \approx 0.96$

This value indicates a very high degree of correlation between the predicted and the actual academic performance using year 1 data. Similarly R^2 computed using year 2, year 3, year 4 and year 5 data are 0.97, 0.99, 0.98 and 0.96 respectively. The tabulation for the computations is given on appendix E, F, G and H respectively. These values, being higher than 0.5 indicate very high level of accuracy for the prediction algorithm. This means it can be relied upon to make decisions regarding the admissions of students into HAILs.

The graphical representation of the high degree of correlation between the predicted and the actual academic performance using year 5 academic data is given on Figs. 6.

In Fig. 6 the predicted and actual academic performance using students' year 1data are plotted together. The closeness of the distribution shows a very high degree of correlation. In Fig. 4.7, a very high degree of correlation can be noticed between the CGPA of 1.90 and 2.99. This corresponds to between 20 and 90 students. In Fig. 4.8, the highest correlation is at CGPA of between 1.89 and 2.89 and secondly at between 3.65 and 4.25.

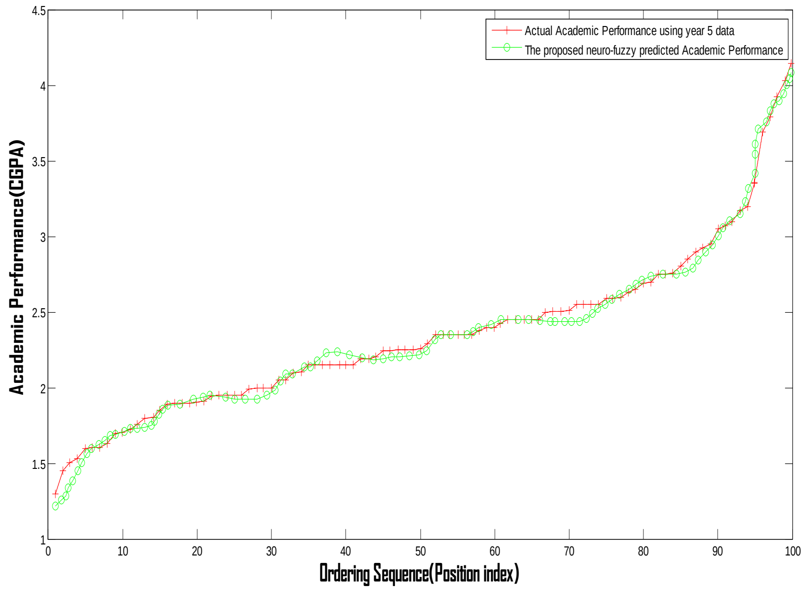


Fig. 7: Graph showing correlation of Neuro-fuzzy Predicated Academic Performance with Actual Academic Performance using Year 5 data

XIII. CONCLUSION

This study recognizes the importance of a computerized intelligent algorithm to provide decision support for admission. With the traditional admission process the decision is solely based on UTME and Post-UTME scores, given that the candidate had met the O- Level requirements. In this work a five layer Adaptive Neuro fuzzy Inference System (ANFIS) was modeled for the prediction of the academic performance of candidates seeking placements into HAILs. This intelligent model was designed to provide decision support in the admission of suitable candidates into HAILs. The developed ANFIS model predicted that 70% of the candidates sampled will be of very poor academic performance (with a CGPA of below 2.5), hence deemed unsuitable for admission into HAILs. This prediction was confirmed with the actual performances of these students in year 1, 2, 3, 4 & 5 on the basis of CGPAs. The accuracy of the model was evaluated on the basis of the statistical deviation of the predictions from the actual performance. In this case, accuracy requires that the predicted and actual academic performance have to be correlated. The computational technique of multi regression is used to find the degree of correlation (or variance) between the predicted dataset and the observed dataset. Validation of the prediction using year 1, 2, 3, 4 and 5 CGPAs indicates coefficients of multi determination R^2 of approximately **0.96, 0.97,0.99, 0.98 and 0.96** respectively. These values show a high degree of correlation between the predicted and the actual academic performance. In other words, the correlation shows that the 70% poor academic performance predicted is in agreement with actual outcome of the academic engagement of the affected students. Making decision based on this prediction means that these students should not have been given admission in the first place. The findings indicate that basing the decision for admission without the support of an intelligent computational structure (like the ANFIS developed in this work), but solely on UTME and Post-UTME scores is not optimal.

REFERENCES

[1] Adeyemi, T. O. (2010) Credit in Mathematics in Senior Secondary Certificate Examinations as a Predictor of Success in Educational Management in Universities in Ekiti and Ondo States, Nigeria. *Middle-East Journal of Scientific Research,* 5 (4), 235-244.

[2] Al Alwan IA. (2009) Association Between Scores in High School, Saudi National Aptitude & Achievement Exams and Early Performance in Health Science College. *Saudi J Kidney Dis Transpl*. 20(3):448-53.

[3] Arora, N., & Saini, J.R., (2013) A Fuzzy Probabilistic Neural Network for Student's Academic Performance Prediction, *International Journal of Innovative* Research in Science, Engineering and Technology, 2(9), 4425-4432.

[4] Burton, N.W. and Ramist, L. (2001) Predicting success in college: SAT® studies of classes graduating since1980 (College Board Research Report No. 2001–002.)New York: College Board. www.collegeboard.com.Dated:15-07-2006

[5] Conard, M. A. (2006) Aptitude is not enough: How personality and behavior predict academic performance. Journal of Research in Personality, 40, 339–346

[6] Cullen, M.J., Sackett, P.R., & Lievens, F.P. (2006) Threats to the operational use of situational judgment tests in the college admission process. *International Journal of Selection and Assessment,* 14, 142-155.

[7] Cunningham, J. W. (1982) Generating interactions between schemata and text. In J. A. Niles & L. A. Harris (Eds.), New inquiries in reading research and instruction (pp. 42-47). Rochester, NY: National Reading Conference.

[8] Curtis D.A., Lind S.L., Brear S., Finzen F.C. (2007) The correlation of student performance in preclinical and clinical prosthodontic assessments. *J. Dent. Educ.* 71:365-372.

[9] De, Winter, J. C. F., & Dodou, D. (2011) Predicting academic performance in engineering using high school exam scores. *International Journal of Engineering Education, 27*, 1343–1351.

[10] Fang, Ko, Chien, and Yu (2013) Assessing medical students' performance in core competencies using multiple admission programs for colleges and universities: from the perspective of multi-source feedback.. *Biomed Journal*. 2013 Jul-Aug;36(4):188-97.

[11] Garton, B. L., Dyer, J.E., & King, B.O. (2000) The Use of Learning style and admission criteria in predicting academic performance and retention of college freshmen. *Journal of Agricultural Education*, Vol. 41 Issue 2, 2000, pages 46-53

[12] Goodman, R.. Higgins,C., Miller, J., and Smyth. P. (1992) Rule-based neural networks for classification and probability estimation . Neural Computation 4 (6) pp., 781-804

[13] Hakkienen, L. (2004) Do university entrance examination predict academic achievement? Labour Institute for Economic Research. Discussion Paper 205.

[14] Hoefer, P., & Gould, J. (2000) Assessment of Admission Criteria for Predicting Students' Academic Performance in Graduate Business Programs. *Journal of Education for Business*, 75(4), 225-229.

[15] Iuliana Ianus (2001) Prediction of Freshmen Academic Performance, a technical report submitted to the Department of Statistics Carnegie Mellon University, March, 2001

[16] Naik, B. and Ragothaman, S. (2004) Using Neural Networks to predict MBA student success, *College Student Journal*, vol. 38, no. 1, Pg. 143-149

[17] O'Connor, M.C., Paunonen, S.V.(2007) Big Five personality predictors of post-secondary academic performance. Personality and Individual Differences, 2007, 43, 971–990.

[18] Oladokun, V. O., Charles-Owaba. O. E. & Adebanjo, O. E. (2008) Predicting Student's Academic performance using artificial neural network: A case study of an engineering course. *The pacific Journal of Science and Technology*, 9 (1) pp. 72-79.

[19] Veloski J, Callahan C, Gang Xu, Hojat M, Nash DB. (2000) Predicting students' performance on licensing examinations during medical school and afterwards. Acad Med 75:S28–S30.

[20] Wilson, T. (1999) A Student Selection Method and Predictors of Success in a Graduate Nursing Programme. *Journal of Nursing Education*, 38, 183-187.

[21] Woosley, S.A., & Shepler, D.K. (2011) Understanding the early integration experiences of first-generation college students. College Student Journal, 45(4), 700-714.

[22] Z. Zhang. (2000) A flexible new technique for camera calibration. IEEE Transactions on Pattern Analysis and Machine Intelligence, 22(11):1330-1334.