Web-Based Neural Network Model for University Undergraduate Admission Selection and Placement

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ABSTRACT

The number of applicants who apply for University admission through the University Matriculation Examination (UME) organized by the Joint Admission and Matriculation Board (JAMB) in Nigeria is increasing yearly. Unfortunately, the facilities in the Nigerian Universities have not been expanding commensurately with the increasing number of applicants. Consequently, large numbers of applicants have to be screened yearly by University Admission Officers in order to select the few that their universities' facilities can support. Under this scenario, Admission Officers have to manually evaluate every candidate's data against the set admission requirements before selecting the few successful ones. This manual admission processing system exhibits three major problems, namely: it is laborious to manually evaluate the data of a very large number of candidates only to end up selecting less than 15% of them; most candidates are dropped off immediately if they fail to meet the admission requirements for their chosen course whereas, they could have met admission requirements for some other courses for which they could have been considered for placement; and the admission screening procedure is not transparent to the applicants and as such, many unsuccessful applicants find it difficult to believe that they are not offered admission for objective reasons.

An effort towards developing a system that can take care of these problems is therefore a step in the right direction. This model is therefore being presented to provide a time-efficient, detailed, and unbiased automated procedure for selecting the most qualified candidates for admission into universities, ensuring that candidates who fail to meet some of the admission requirements for their chosen course are automatically considered for placement into another course for which they may meet the admission requirements, provided there are vacant positions, and providing an avenue for a candidate self-screening admission system.

(Keywords: automated selection, matriculation, entrance examination, University Matriculation Examination, UME, JAMB, higher education)

INTRODUCTION

Nigeria's desire for education dates back to the pre-independence period, when the colonial government in Lagos in 1887 requested that the University of London extended its examination facilities to Nigerian candidates (Omolewa, 1981). Early graduates in Nigeria went through the University of London correspondence matriculation examinations. Most Nigerians in this period passed through correspondence courses offered by British institutions such as Rapid Result College and Wosley Hall to obtain their general certificates in education, which was a pre-requisite to university admission.

The establishment of Yaba Higher College in 1932 marked the beginning of higher education in Nigeria. The purpose was to produce assistants who would relieve colonial administrators of menial tasks. Due to problems in admission and administration, the colonial government then set up the Elliot Commission to specifically examine the principles which would guide the promotion of higher education, learning, and research and the development of universities in the colonies. The commission included three West Africans who traveled extensively for three months and later submitted two reports (majority and minority). The majority report recommended that a university college should be set up in Nigeria, the former Gold Coast (now Ghana), and Sierra Leone. Five of the fourteen members of this commission wrote a minority report in which they criticized the establishment of three university colleges on the basis that there were not enough students to support these colleges (Adesina, 1988). This created additional problems in the colonies and a second commission, the Asquith Commission, stressed in its reports that the new colonial universities should initially be university colleges rather than full universities. In this scenario the universities would not be free to set their own examinations or grant their own degrees but would be affiliated with foster-parent universities.

University College, Ibadan was established in 1940. As a University College, the programs offered there and then were narrow as the colonial administration did not pursue an agenda of training high-level manpower for many of the professions.

In 1960, the Ashby commission recommended the establishment of regional universities in the then three regions of the country. In the East, the University of Nigeria (1960); in the North, Ahmadu Bello University (ABU), Zaria (1962); and in the West, the University of Ife (1961) (now Obafemi Awolowo University) while the University College Ibadan was granted full-fledged University status in 1962. Also in 1962, the University of Lagos, Akoka was established and as a city university, it provided courses in humanities, social sciences, medicine, law, and engineering and also offered part-time programs for working students. The University of Benin was established in 1970. These six universities constitute Nigeria's first-generation universities (Adesina, 1988).

Higher education history in Nigeria is amazing as it developed from one University College in 1960 to now over one hundred and fifty tertiary institutions made up of universities, polytechnics, and colleges of education with an aggregate student population of over 800,000 (full and part time).

There are well over 500,000 candidates seeking placements into universities annually in Nigeria and less than 15% of them secure admission. Admission decisions are made by educational institutions by considering a variety of factors. Some of the evaluation criteria normally used are: UME subject combinations; university's admission requirements; overall scores in UME results; five credits obtainable in O/Level certificates (not more than two sittings); catchments area considerations; and educationally disadvantaged area considerations.

On receiving the UME results by the university, the Admission Officer manually evaluates every candidate's data against the various admission requirements before taking admission and placement decisions. This process is quite enormous and costly in terms of resources and processing time. And, as with other manual processes, it is fraught with inaccurate decisions resulting from avoidable human processing errors and at times deliberate manipulations to achieve some unwholesome personal aims like admitting unqualified candidates. Therefore, in this paper, a web-based neural network model for university undergraduate student admission and placement into Nigerian Universities is presented.

The model is to provide a time-efficient, detailed and unbiased automated procedure for selecting the most qualified candidates for admission into universities, ensure that candidates who fail to meet some of the admission requirements for their chosen course are automatically considered for placement into another course for which they meet the admission requirements provided there are vacant positions, and to provide an avenue for a candidate self-screening admission system.

RELATED WORKS

Statistical procedures, such as discriminant analysis and regression analysis are traditionally used for predicting potential academic success of applicants (Graham, 1991). The predictive validity study may help make admission or selection procedures more efficient and effective (Powers and Lehman, 1983; Dobson et al., 1999; Lievens and Coetsier, 2002). However, the selection criteria used in higher education admission processes varies widely among programs and no consistent conclusions can be reached on the predictive values of these criteria (Wilson, 1999). This may partly be due to the fact that the predictive validity of the selection instruments is not in itself sufficient for an assessment of the validity of a selection, although it can be a critical factor (Wolming, 1999).

In this paper, prediction is not the stated purpose for the student selection problem. The selection of applicants is made on the grounds of the candidates' merits (performance evaluation) assessed by an interview process and his/her academic background, based on a given set of criteria in accordance with the requirements of the undergraduate academic program.

Morris and his colleagues at the University of Minnesota attempted to predict the GPA of University of California students using neural networks (Morris and Gibsson, 2004). In achieving their objectives, they compared three different network topologies of which the average error rate for the network model was used within the range of 8 inputs and 1 output as the lowest. The results obtained show that the attributes used were not adequate and they proceeded to increase the attributes.

The first network design consists of three inputs; gender, sleep and alcohol, two hidden layers of eight and five nodes, and one output node. The model works with the aid of training so as to predict the actual GPAs, once it is fed with appropriate variables, data, or attributes.

The second model phase of the neural network used in their work contained eight input nodes, which were comprised of the hidden layer with 6 nodes, and 4 Boolean output nodes. This particular approach was used to determine if the model can effectively categorize a student's GPA by the 8 given attributes. Each of the output ranges correspond to a range that falls within the standard grade scale between 0 to 1.0; 1.01 to 2.0; 2.01 to 3.0; and 3.01 to 4.0. Furthermore, to train the network to meet the set goal, each of the output nodes was initialized to the correct value using the student's GPA of 3.5 corresponding to {false, false, false, true}. The basic idea here was used to classify given GPA's into A, B, C or D etc. (Chris et al., 2004).

In the third network, the model equally featured eight input nodes, two hidden layers of seven nodes each, and one output node. The output, as in the first network, was the actual GPA prediction and the essence of this model was to integrate all of the attributes into the prediction process.

Above all, the three networks each had their own merits and demerits; the first model only incorporated the three attributes after training the network. It was discovered that there was no correlation between the GPA and gender, that is, gender is insignificant in the prediction process. The second network showed that there was a low validation rate, therefore, it did not predict the actual GPA. This may be due to some problems associated with the network. And the third network used all the attributes, but the queries showed that overlap and noise were problems. The results finally displayed that the attributes used in the neural networks model were not sufficient to predict GPA. Hence, there are many other attributes that can be added in order to improve the GPA predictions.

Within the last few years, neural networks and classical statistical modeling have often been both compared as predictors of success or failure in various disciplines. Gorr and his colleagues conducted a comparative study of neural network and statistical models for predicting college student's grade point averages (Gorr et al., 1994).

Also, Ashby and Kumar (1996) compared neural networks and discriminant analysis in anticipating defaults among high yield bonds. Both studies revealed that the neural network serves as a better predictor than the discriminant analysis. The use of neural network as a predictor has increased over the past few years. Cripps (1996) equally used a neural network to predict grade point averages of middle Tennessee State University students. According to Carbone and Piras (1998), they opined that the neural network is instrumental in predicting high school dropouts.

In Nelson and Henricksen's study (1994), a neural network used input from the student responses on mathematics placement examination given to incoming students at Ball State University and outputs the mathematics course in which each student should be placed. Hardgrave et al. (1994) used neural network for predicting MBA students' performance for admission in a graduate program and the study show that the result obtained is promising. Hence the implementation of neural networks as a prediction tool for educational placement and assessment continues to increase.

Sheel and his colleagues also carried out a study on implementing a technique that can be used to classify college student placement into the appropriate mathematics course (Sheel et al, 2002). In their work, they examined the alternative placement strategies using regression analysis. The cumulative high school grade point average, mathematics SAT, and the final grade in Algebra II were found to be the best predictors of success on a mathematics placement examination. Using these features, entry-level mathematics placement based on networks was later contrasted with discriminant analysis, and proposed as an alternative to testing. Results obtained showed that neural networks outperformed classical discriminant analysis in predicting the recommended mathematics placement.

As technology continuously progresses, methodologies evolve to enhance abilities to perform arduous tasks more expediently. Utilizing modern computing technologies not only make completing tasks more efficient, but also often achieve a higher degree of accuracy than human being does. For instance, classifying students placement test.

The entry-level mathematics courses for placement are as follows: Math 130; Intensive College Algebra, Math 131; College Algebra, Math 133; Trigonometry and Analytic Geometry, and Math 160; and Introductory Calculus.

All colleges within Coastal Carolina University, except the Wall School of Business are utilizing the examination created by the mathematics department. Students entering the College of Business are assigned to a mathematics class according to their academic achievement in secondary education. The neural networks and discriminant analysis represent techniques that can be employed for membership classification.

This study compares the effectiveness of placements based on neural network classifications and discriminant analyses with the more traditional manual test-based placement. The results for both the neural approach and discriminant analysis are compared to the results obtained by the mathematics placement test. If a trained neural network or prediction equation based on discriminant analysis yielded statistically similar results to the mathematics placement test, then one or the other could be used for entry-level placement.

However, in this series of experiments, supervised feed-forward neural networks were chosen as the network model. The networks were trained using data for entry-level college students grouped according to their performance on the mathematics placement examination. The student's high school grade point average, SAT mathematics score, and high school Algebra II scores were used in the input layer. The output layer consisted of four nodes, representing courses into which the students may be placed in the mathematics placement exam. In this experiment, recurrent back-propagation is used to train the network.

In achieving their goal, 458 student records were randomly ordered and assigned to two equal sets. The first group was to train the neural networks and to create the discriminant analysis predictive equation. The second data set was used to test the trained neural networks and the predictive discriminant analysis equation. Both methodologies used the overall high school GPA, the SAT mathematics score, and the final grade in Algebra II as inputs, with the mathematics placement result as the output variable.

The topology chosen for the back-propagation network consisted of 3-inputs, 10-hidden layers, and 10-output networks, with ten nodes ensembles of weak classifiers generated under identical conditions (Renner and Lacher, 2000).

The recurrent back-propagation neural network significantly outperformed the predictive discriminant analysis equation as a tool for placing incoming freshmen into entry-level mathematics course.

Bijayananda and Srinivasan (2004) in their work titled "Predicting MBA performance for admission decisions is crucial for educational institutions" evaluated the ability of three different models – neural networks, logit, and probit to predict MBA student performance in graduate programs. In the work, 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.

Three tables were used for the experiment and the results of the predictions of the neural networks and statistical models used showed that the neural network model outperformed the traditional statistical models and is a useful tool to predict MBA student performance. The overall results suggest that the classification accuracy (and implied predictive power) of the neural network model is 89.13 percent and that of the logit and probit models are 72.83 percent and 73.37 percent respectively.

The use of a non-linear model such as the neural network allows administrators to specifically incorporate uncertainties into the decision making process. The traditional check list and formula approach does not permit this flexibility. To assess the neural network model's ability to classify students into successful and marginal groups, the predictive ability of the neural network model was compared with two statistical models namely logistic regression (logit) and probit (Wright and Palmer 1994) and it was shown that the use of a neural network model can support and potentially improve decision making by MBA directors and deans.

THE MODEL

Selection of applicant is made on the candidates' merits assessed by JAMB coupled with performance of the candidates in National Examinations Council (NECO) and West African School Certificate (WASC) Ordinary Level examinations in not more than two sittings and other academic background based on a given set of criteria in accordance with the requirements of the undergraduate academic programs in all disciplines. Artificial neural networks have attracted attention in the last few years, hence the adoption of artificial neural network in this research.

Let c_1, c_2, …, c_k be the courses potential students applied for; U_{kj} and J_{ij} be the UME subjects requirements and JAMB's UME subjects sat for by the potential student s_i for the course c_k respectively. Let also O_{kj} be the O/Level subjects combination admission requirements for the course c_k and A_{ij} and B_{ij} represent the O/Level grades obtained by the potential student s_i in not more than first and second sittings respectively such that $i, j, k = 1, 2, \ldots, n$.

U_{kj}, J_{ij}, O_{kj}, A_{ij}, and B_{ij} could be represented as sparse matrices as follows:

$$U_{kj} = \begin{bmatrix} u_{11} & u_{12} & \cdots & u_{1m} \\ u_{21} & u_{22} & \cdots & u_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ u_{n1} & u_{n2} & \cdots & u_{nm} \end{bmatrix}; u_{kj} = \begin{cases} 1, \mathit{if}\ u_{kj}\ \mathit{is\ compulsory\ for}\ c_k \\ 2,3\ \mathit{if}\ u_{kj}\ \mathit{is\ group\ of\ subjects\ for}\ c_k \\ 0, \mathit{if}\ u_{kj}\ \mathit{not\ required\ for}\ c_k \end{cases}$$

$$J_{ij} = \begin{bmatrix} j_{11} & j_{12} & \cdots & j_{1m} \\ j_{21} & j_{22} & \cdots & j_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ j_{n1} & j_{n2} & \cdots & j_{nm} \end{bmatrix}; j_{ij} = \begin{cases} 1, \mathit{if}\ j_{ij}\ \mathit{is\ registered\ and\ sat\ for\ by}\ s_i \\ \\ 0, \mathit{if}\ j_{ij}\ \mathit{not\ registered\ for} \end{cases}$$

$$O_{kj} = \begin{bmatrix} o_{11} & o_{12} & \cdots & o_{1m} \\ o_{21} & o_{22} & \cdots & o_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ o_{n1} & o_{n2} & \cdots & o_{nm} \end{bmatrix}; o_{kj} = \begin{cases} 1, \mathit{if}\ o_{kj}\ \mathit{is\ compulsory\ for}\ c_k \\ 2,3\ \mathit{if}\ o_{kj}\ \mathit{is\ group\ of\ subjects\ for}\ c_k \\ 0, \mathit{if}\ o_{kj}\ \mathit{not\ required\ for}\ c_k \end{cases}$$

$$A_{ij} = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1m} \\ a_{21} & a_{22} & \cdots & a_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ a_{n1} & a_{n2} & \cdots & a_{nm} \end{bmatrix}; a_{ij} = \begin{cases} 1, \mathit{if}\ 2 \le a_{ij} \le 4\ (a_{ij}\ \mathit{passed\ at\ credit\ level\ by}\ s_i) \\ \\ 0, \mathit{if}\ a_{ij} < 2\ (a_{ij}\ \mathit{failed\ or\ not\ attempted\ by}\ s_i) \end{cases}$$

$$B_{ij} = \begin{bmatrix} b_{11} & b_{12} & \cdots & b_{1m} \\ b_{21} & b_{22} & \cdots & b_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ b_{n1} & bn2 & \cdots & b_{nm} \end{bmatrix}; b_{ij} = \begin{cases} 1, \mathit{if}\ 2 \le b_{ij} \le 4\ (b_{ij}\ \mathit{passed\ at\ credit\ level\ by}\ s_i) \\ \\ 0, \mathit{if}\ b_{ij} < 2\ (b_{ij}\ \mathit{failed\ or\ not\ attempted\ by}\ s_i) \end{cases}$$

These matrices are sparse matrices because for instance, for course c_k, only four UME subjects are to be registered and sat for by potential candidates and whereas there are twenty-one subjects in all.

The UME subjects requirements for course c_k is a row vector $u_{km} = \lfloor u_{k1} \quad u_{k2} \quad \ldots \quad u_{kz} \rfloor$ and $u_{kz} \subseteq U_{kj}, z = 1, 2, .., m.$ Also, the potential candidate s_i's UME subjects for the course c_k is a row vector $j_{ip} = \lfloor j_{i1} \quad j_{i2} \quad \ldots \quad j_{ip} \rfloor$ and $j_{ip} \subseteq J_{ij}, p = 1, 2, .., n.$ The O/Level subjects combination requirement for course c_k as well is a row vector $o_{kq} = \lfloor o_{k1} \quad o_{k2} \quad \ldots \quad o_{kq} \rfloor$ and $o_{kz} \subseteq O_{kj}, q = 1, 2, .., n.$

Finally, the grades obtained by potential candidates in either of first or second sitting at the ordinary level subjects are also vectors such that $a_{ij} \subseteq A_{ij}$, and $b_{it} \subseteq B_{ij}$ respectively.

Figure 1 shows the artificial neural networks for this model. The weights to the models are as shown in the sparse matrices above.

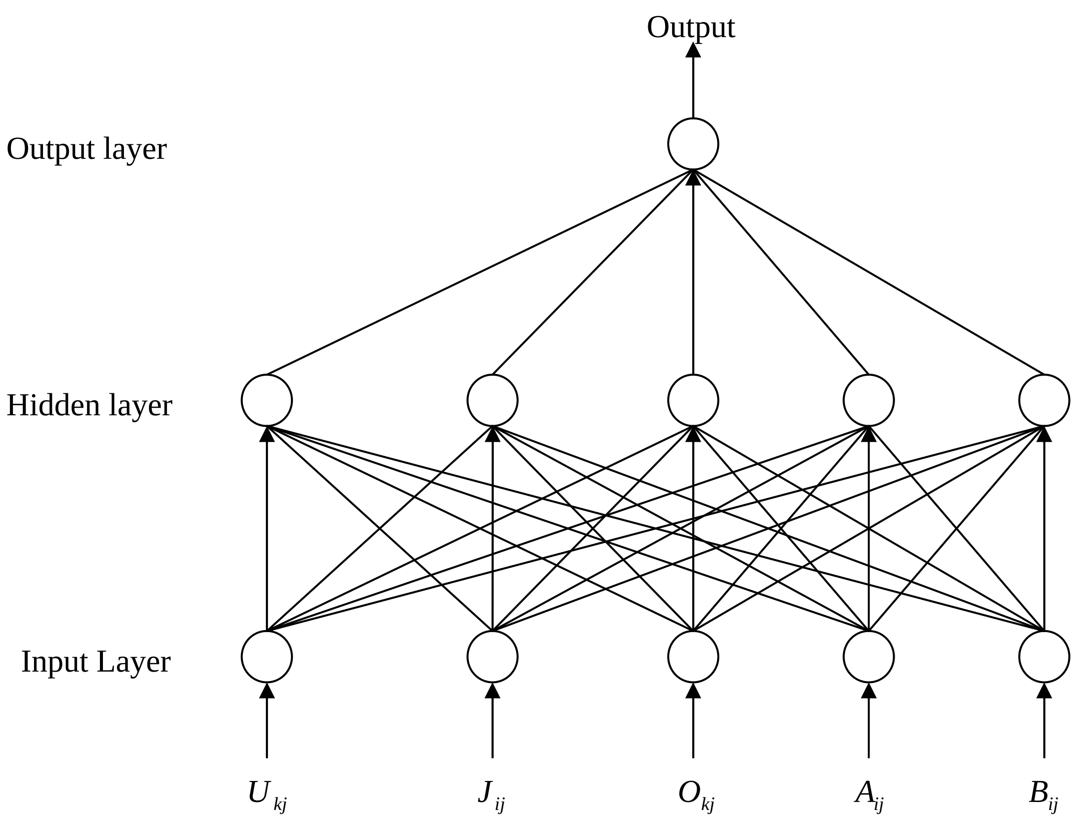

Figure 1: The Artificial Neural Networks Model.

Then for each of the potential candidate s_i that applied for the course c_k, let l = 1, 2, 3 represent compulsory UME subjects and other subject groups from which candidates are expected to select from respectively and $I(l)$ represents the total number of subjects sat for at the JAMB UME examinations.

Therefore, let r equals total number of subjects sat for, for each $U_{kj} = l$ and $l = 1$ (compulsory subjects) such that $I(l) \leq 4$, if

$$U_{kj} \neq J_{ij} \quad \textbf{(1)}$$

process next potential student' data for the course c_k, otherwise

$$X_r = M(J_{ij}) \text{, r = 1, 2, …, 4.} \quad \textbf{(2)}$$

where M is a function that returns the mark obtained by the candidate in the JAMB UME subject J_{ij}. Process the next $U_{kj} = l$.

If $I(l) < 4$ (total number of subjects sat for), then there exists l = 2, 3 such that $U_{kj} = l$ where l represents other subject groups from which candidates ought to have selected $I(l)$ from. Therefore, let $m = l$ = 1, 2, …, I(l) for each l = 2, 3, if $I(l)$ = 0, select next l otherwise for each $U_{kj} = l$, obtain

$$X_r = M(J_{ij}),\ iff\ U_{kj} = J_{ij}. \quad \textbf{(3)}$$

If $I(l) - m > 0$, select the next $U_{kj} = l$. If $m = 0$, select next potential candidate's data for the course c_k. If $\sum_{t=1}^{r} I(t) < 4$, select next l otherwise obtain the $scut\text{-}off_i$ as follows

$$scut-off_i = \begin{cases} 1,\ provided\ \sum_{r=1}^{4} X_r \geq cut-off_k \\ 0,\ otherwise \end{cases} \quad \textbf{(4)}$$

where $\sum_{r=1}^{4} X_r$ represents the total scores obtained by the candidates s_i for course c_k. and $scut\text{-}off_i$ represents student's total UME score $cut\text{-}off_k$ represents cut off score for course k.

If $scut\text{-}off_i$ = 1, define $r = 0$, $z = 0$, j = 1, 2, …, n, for each $O_{kj} = l = 1$ (compulsory ordinary level subjects) such that $N(l) \leq 5$. Let $F(e)$ be a function that returns 1 *iff* a_{ij} or $b_{ij} = O_{kj}$ otherwise it returns 0. If

$$O_{kj} \neq F(a_{ij}) \vee F(b_{ij}) \quad \textbf{(5)}$$

process next potential candidate's data for the course ck, otherwise $z = z + 1$ and process the next O_{kj}.

If $N(l) < 5$ (total number of ordinary level credits obtained), then there exist l = 2, 3 such that $O_{kj} = l$, where l represents other subjects groups where potential student is expected to have O/L credits from. Therefore, let m = l = 1, 2, …, I(l), for each l = 2, 3, if $N(l)$ = 0, select next l otherwise for each $O_{kj} = l$,

$$z = z + 1,\ iff\ O_{kj} = F(a_{ij}) \vee F(b_{ij}) \quad \textbf{(6)}$$

If $N(l) - m > 0$, select next $O_{ky} = l$. If $m = 0$, select next potential candidate's data for the course c_k. If $\sum_{t=1}^{z} I(t) < 5$, select next l. For $z = 5$,

$$adm_i = 1 \quad \textbf{(7)}$$

Select the next potential candidate i for the course c_k otherwise select the next course c_k.

Finally, for placing students whose $adm_i \neq 1$, select each of the students whose $adm_i \neq 1$, for each of the courses c_k, if

$$\sum_{r=1}^{4} X_r \geq cut-off_k \quad \textbf{(8)}$$

equations 1 through 3 and equations 5 and 6 are applied, if equation 7 holds, the candidate is placed into the course and select next course c_k.

For candidate self evaluation the entire equations 1 to 8 are applied to evaluate individual candidate's results against the admission requirements in order to determine whether he qualifies or not. However, it is also possible to perform the candidate's self evaluation process in two stages. The first stage allows the application of equations 1 to 4 to the candidate's UME subjects' scores. This stage is useful for candidates awaiting their ordinary level results. Later, the if he meets the admission requirements and the O/L results are now available, then equations 5 to 8 will only be applied on the ordinary level results as the system keeps the outcome of equation 4 in a database table.

Figure 2 shows the internal working of the above model.

TECHNOLOGICAL APPROACH TO UNIVERSITY UNDERGRADUATE ADMISSION AND PLACEMENT SYSTEM

The technological approach for the development of the system is based on AMP (Apache, MySQL, and PHP) open source solution (Adewale, 2006). Other solutions such as Microsoft's Internet Information Server (IIS) are popular, however, the lack of security and potential higher cost of hardware and maintenance keep them out of reach of many small companies. Rather than spending millions of dollar on licenses and administrative costs, one can choose to run a free software solution. Speed is another significant factor to most of us. The system needs to respond quickly and remain snappy throughout the user's experience. With proper coding techniques, PHP is many times faster than Microsoft's ASP or Sun Microsystems' Java platform.

The university admission and placement system is built around a *three-tier architecture* model (Adewale, 2006). This is shown in Figure 3. At the base of an application is the *database tier,* consisting of the *database management system* that manages the database containing the data users create, delete, modify, and query and MySQL relational database is used to provide the required functionality.

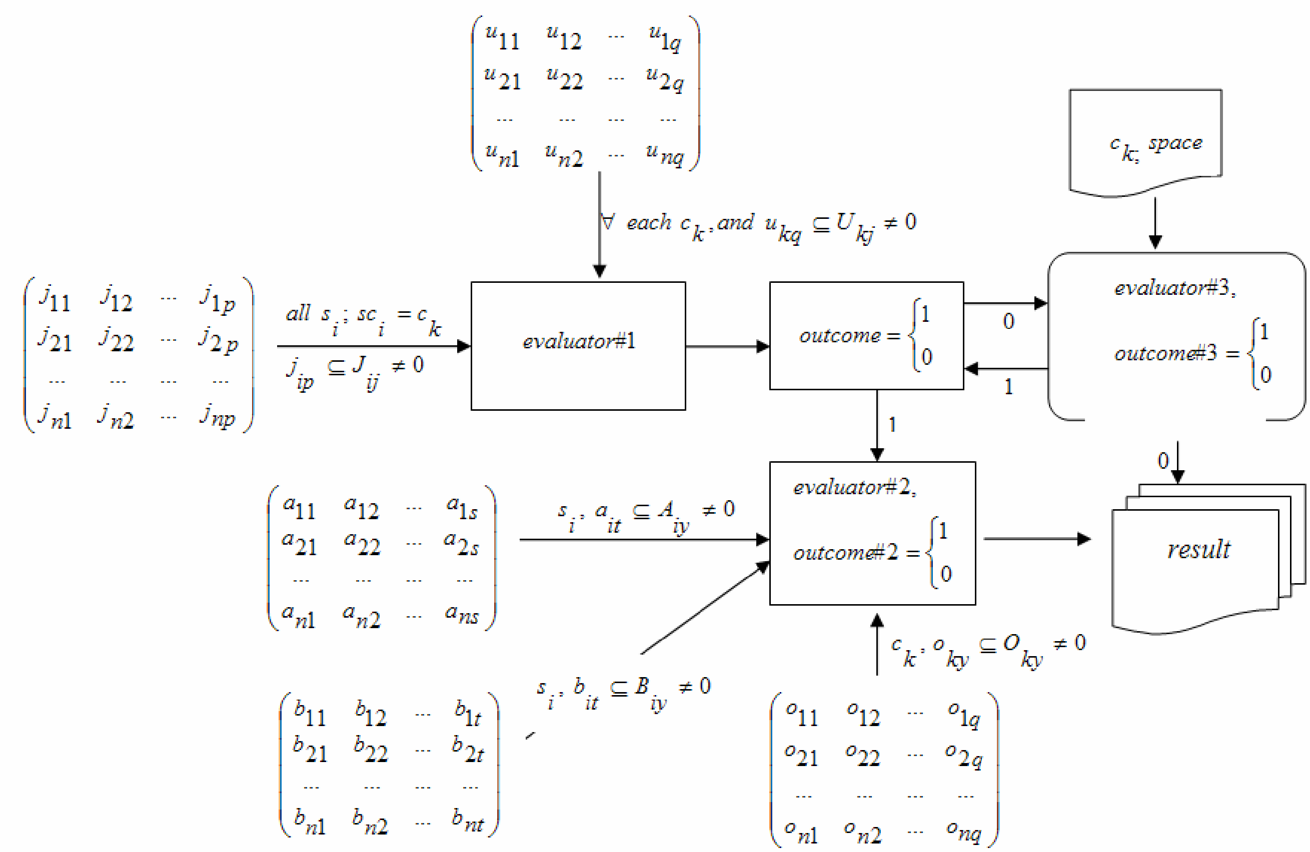

Figure 2: The Internal Working of the Model.

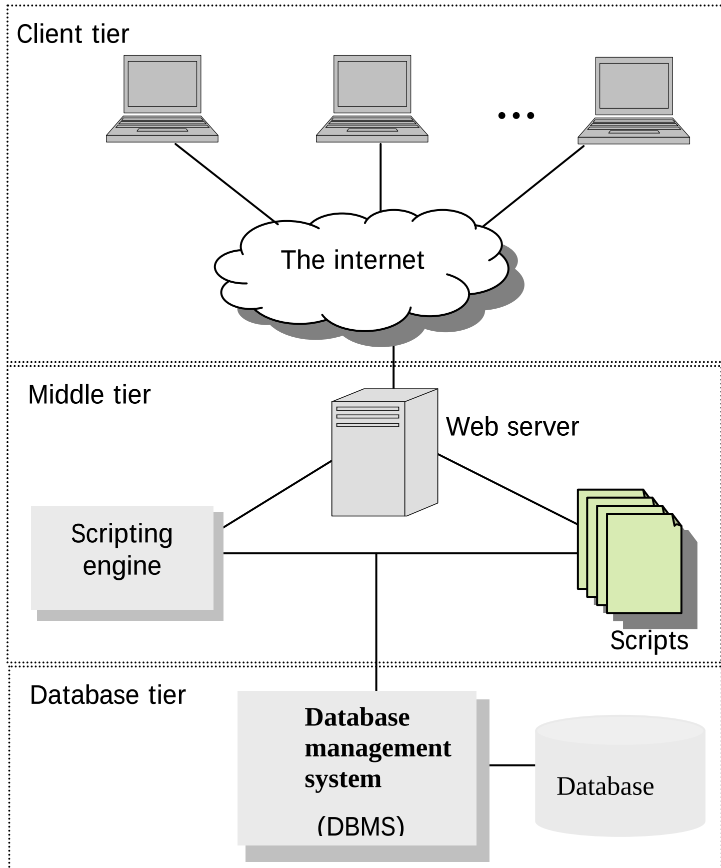

Figure 3: Three-Tier Architecture Model.

A relation is customarily referred to as a file and generally perceived and represented by a set of structured tuples. Each tuple of a relation corresponds to a record in a file and attributes correspond to fields within a record. The general form of a relation is given by R[A_1, A_2, …, A_{k+1}, …, A_{n-1}, A_n]. The name of the relation is represented by R, the set {$A_{i,\ i=1,2,\ \ldots,\ n}$} represents the attributes of the relation R. The database objects used in the university admission and placement system are:

course_ume_req[course_code, u_{k1}, u_{k2}, …, u_{k21}, l_2, l_3];

course_o_level_req[course_code, o_{k1}, o_{k2}, …, o_{k21}, l_2, l_3];

cand_ume_table[cand_ume_no, exam_no, j_{i1}, j_{i2}, …, j_{i21}];

cand_first_sit[cand_ume_no, exam_no, a_{i1}, a_{i2}, …, a_{i21}];

cand_second_sit[cand_ume_no, exam_no, b_{i1}, b_{i2},…, b_{i21}];

cand_process_table[cand_ume_no, course_code, ume_score, scut_off, admin, placement, plmrem, final_course];

quota_cut_off[course_code, quota, cut_off, batch].

Built on top of the database tier is the complex *middle tier*, which contains most of the application logic and communicates data between the other tiers. The web server is apache and it is running under Windows operating system which is used to achieve a secured client-server communication. The scripting engine uses server-side PHP functions to communicate with the database. PHP scripts are used to co-ordinate all the procedures in the system. PHP handles data which are passed from the html forms in the way that structured query language formed are sent to the database and then results of the queries are processed and passed back in an html document format. On top is the *client tier*, usually web browser software that interacts with the application. The formality of describing most web database applications as three-tier architectures hides the reality that the applications must bring together different protocols and software. When we use the term *the web*, we mean three major distinct standards and the tools based on these standards: the Hypertext Markup Language (HTML), the Hypertext Transfer Protocol (HTTP), and the TCP/IP networking protocol suite. HTML works well for structuring and presenting information using a web browser application. TCP/IP is an effective networking protocol that transfers data between applications over the Internet and has little impact on web database application developers. The problem in building web database applications is interfacing traditional database applications to the web using HTTP. This is where the complex application logic is needed.

Entry point to some of the university admission and placement system requires users' authentication and authorization because of the sensitivity of the admission process. Since users access the system remotely, therefore a built-in security system forces users to login first.

There are several alternatives to users' authentication. These alternatives include among others HTTP basic authentication and PHP session schemes. In implementing HTTP basic authentication, one either has to properly configure it through web server such as using *.htaccess* file on an apache server or duplicate the functionality through the use of the PHP *Header* function. Although the HTTP mechanism is acceptable, even with a proper set up HTTP authentication has many shortcomings such as lack of security features (inactivity timeout); and developer-friendly benefits (the ability to display secure/non-secure data easily on the same page).

As a result of the above mentioned shortcomings, a PHP session authentication is used in the system to control access to most of the university admission and placement system's sensitive areas while at the same time providing a more useful and clean implementation. Sessions are a mechanism that allows PHP to preserve state between executions.

Because we want to tie a user to a session, the user's username and password are stored in a MySQL database table and authenticated against that. There are four main elements to the system user authentication module: user registration, login and logout, changing password, and resetting passwords. A valid user or admission officer could perform each of these elements. To register, a user supplies his/her user identification number, and the *preferred username*, *password* and *password confirmation* via an html form, and if the user identification number is found in the user table and both password and password confirmation are the same, it then registers the username and password in the user table.

Registered users can now login by supplying valid username and password details into an html form and submitting it. The entries will be processed and the user will be logged on if the authentication is successful. Users are also allowed to change their passwords and in addition to this, the system also deals with the common situation in which a user has forgotten a password.

SYSTEM IMPLEMENTATION

Under the current admission process, each admission officer manually evaluates every candidate's data against the various admission requirements before making admission and placement decisions. This process is quite costly in terms of resources and processing time. And, as with other manual processes, it is fraught with inaccurate decisions resulting from avoidable human processing errors and at times deliberate manipulations to achieve some unwholesome personal aims like admitting unqualified candidates.

The university admission and placement system was implemented using the values in Table 1 to Table 5. Tables 1 to 5 show some of the database tables required in order to evaluate potential candidates against the university admission requirements. Table 1 and Table 2 show the course UME and O/L admission requirements respectively.

Tables 3 to 5 show potential candidates' UME subjects attempted, O/L grades in either first or second sitting respectively. Admission process module applies equations 1 to 8 to evaluate Tables 3 and 5 against Tables 1 and 2 to obtain Table 6. The results obtained from the system demonstrated that the system is able to meet its objectives.

Table 1: UME Admission Requirements Table

course code	U_{k1}	U_{k2}	U_{k3}	U_{k4}	U_{k5}	U_{k6}	U_{k7}	U_{k8}	U_{k9}	U_{k10}	U_{k11}	U_{k12}	U_{k13}	U_{k14}	U_{k15}	U_{k16}	U_{k17}	U_{k18}	U_{k19}	U_{k20}	U_{k21}	cut_off_k	I_2	I_3
	Eng	mat	phy	bio	agr	eco	geo	che	add	sta	tdr	com	enl	crk	Frc	his	Acc	pos	gov	fat	hec			
CSC	1	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	210		
MTS	1	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	200		
PHY	1	1	1	2	2	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	220	1	
FWT	1	3	3	2	2	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	180	1	1
MCB	1	3	3	2	2	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	200	1	1
BCH	1	3	3	2	2	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	210	1	1
ICH	1	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	235		
AGY	1	1	2	2	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	230	1	
AGP	1	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	200		
MET	1	1	1	0	0	0	2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	180	1	
BIO	1	3	3	2	2	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	200	1	1

Table 2: O/L Admission Requirements Table

course_code	O_{k1}	O_{k2}	O_{k3}	O_{k4}	O_{k5}	0_{k6}	O_{k7}	O_{k8}	O_{k9}	O_{k10}	O_{k11}	O_{k12}	O_{k13}	O_{k14}	O_{k15}	O_{k16}	O_{k17}	Q_{k18}	O_{k19}	O_{k20}	O_{k21}	I_2	I_3
	eng	mat	phy	bio	agr	eco	geo	che	adm	sta	tdr	com	enl	crk	frc	his	acc	pos	gov	fat	hec		
CSC	1	1	1	2	2	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	2	
MTS	1	1	1	2	2	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	2	
PHY	1	1	1	2	2	2	2	1	2	2	2	2	2	2	2	2	2	2	2	2	2	1	
FWT	1	1	1	2	2	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	
MCB	1	1	1	2	2	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	
BCH	1	1	1	2	2	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	
ICH	1	1	1	2	2	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	
AGY	1	1	1	2	2	0	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	
AGP	1	1	1	2	2	2	2	1	2	2	2	2	2	2	2	2	2	2	2	2	2	1	
MET	1	1	1	3	3	3	2	2	3	3	3	3	3	3	3	3	3	3	3	3	3	1	1
BIO	1	1	1	2	2	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	

Table 3: Candidate JAMB UME Table

STD_JNO	course_code	J_{i1}	J_{i2}	J_{i3}	J_{i4}	J_{i5}	J_{i6}	J_{i7}	J_{i8}	J_{i9}	J_{i10}	J_{i11}	J_{i12}	J_{i13}	J_{i14}	J_{i15}	J_{i16}	J_{i17}	J_{i18}	J_{i19}	J_{i20}	J_{i21}
		eng	Mat	phy	bio	agr	eco	geo	che	add	sta	tdr	com	enl	crk	Frc	his	acc	pos	gov	fat	hec
05_214	CSC	1	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
05_300	MTS	1	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
05_765	FWT	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
05_140	CSC	1	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
05_907	BIO	1	1	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
05_567	CSC	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
05_490	MTS	1	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
05_200	BCH	1	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
05_696	CSC	1	0	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
05_800	ICH	1	1	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
05_1254	MCB	1	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
05_915	AGP	1	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
05_700	ICH	1	0	1	1		0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
05_2345	MTS	1	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
05_17	MTS	1	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
05_249	FWT	1	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
05_1000	CSC	1	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
05_9000	BIO	1	1	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
05_911	CSC	1	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
05_1010	MTS	1	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
05_1100	BCH	1	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
05_980	CSC	1	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
05_115	ICH	1	1	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
05_209	MCB	1	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
05_715	MTS	1	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
05_2111	MTS	1	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
05_7100	MTS	1	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
05_7214	FWT	1	1	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
05_3000	CSC	1	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
05_3477	BCH	1	1	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
05_3218	MCB	1	1	1	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
05_243	ICH	1	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
05_915	MTS	1	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
05_616	MTS	1	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
05_203	FWT	1	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 4 :Candidate O/L First Sit Table

STD_JNO	STUD_NO	a_{i1}	a_{i2}	a_{i3}	a_{i4}	a_{i5}	a_{i6}	a_{i7}	a_{i8}	a_{i9}	a_{i10}	a_{i11}	a_{i12}	a_{i13}	a_{i14}	a_{i15}	a_{i16}	a_{i17}	a_{i18}	a_{i19}	a_{i20}	a_{i21}
		eng	mat	phy	bio	agr	eco	geo	che	adm	sta	tdr	com	enl	crk	frc	his	acc	pos	gov	fat	hec
05_214	200201234	1	2	4	3	4	0	1	4	3	0	0	0	0	0	0	0	0	0	0	0	0
05_765	19990224	2	0	3	1	0	3	2	3	0	0	4	0	0	0	0	0	0	0	0	0	0
05_140	2002097	1	4	3	2	4	3	4	4	0	0	0	0	0	0	0	0	0	0	0	0	0
05_567	2000034	3	3	3	0	3	4	1	4	0	0	0	0	0	0	0	0	0	0	0	0	0
05_490	20020997	1	3	4	4	4	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0
05_696	1998020	0	2	4	1	2	0	1	4	3	0	0	0	0	0	0	0	0	0	0	0	0
05_800	20000570	2	4	3	0	4	4	4	3	4	0	0	0	0	0	0	0	0	0	0	0	0
05_1254	200201730	1	0	4	3	1	2	1	3	0	0	0	0	0	0	0	0	0	0	0	0	0
05_200	2003045	2	4	4	3	4	2	2	3	0	0	0	0	0	0	0	0	0	0	0	0	0
05_1915	2001066	1	0	1	4	2	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
05_117	1988012	2	2	2	2	2	0	4	0	1	0	0	0	0	0	0	0	0	0	0	0	0
05_249	199901447	0	2	4	1	2	0	1	4	3	0	0	0	0	0	0	0	0	0	0	0	0
05_1000	2001017	4	4	4	4	4	0	4	4	4	0	0	0	0	0	0	0	0	0	0	0	0
05_9000	2001067	2	0	3	1	0	3	2	3	0	0	4	0	0	0	0	0	0	0	0	0	0
05_911	2000067	4	4	3	2	4	1	4	4	0	0	0	0	0	0	0	0	0	0	0	0	0
05_1010	19970200	2	4	4	3	4	2	2	3	0	0	0	0	0	0	0	0	0	0	0	0	0
05_715	2000010	2	4	3	0	4	4	4	3	4	0	0	0	0	0	0	0	0	0	0	0	0
05_2111	20000120	4	4	3	3	4	4	0	3	4	0	0	0	0	0	0	0	0	0	0	0	0
05_7100	20020170	0	2	4	1	2	0	1	4	3	0	0	0	0	0	0	0	0	0	0	0	0
05_3477	2001015	4	2	4	1	2	3	1	4	0	0	0	0	0	0	0	0	0	0	0	0	0
05_3218	19960100	4	4	3	2	4	1	4	4	0	0	0	0	0	0	0	0	0	0	0	0	0
05_243	19970600	3	3	4	2	2	2	2	2	0	0	0	0	0	0	0	0	0	0	0	0	0
05_915	2003070	2	4	3	0	4	4	4	3	4	0	0	0	0	0	0	0	0	0	0	0	0
05_616	19950271	2	4	4	3	4	2	2	3	0	0	0	0	0	0	0	0	0	0	0	0	0
05_203	19960169	2	4	1	2	0	4	2	2	2	0	0	0	0	0	0	0	0	0	0	0	0

Table 5: Candidate O/L Second Sit Table

STD_JNO	STUD_NO	b_{i1}	b_{i2}	b_{i3}	b_{i4}	b_{i5}	b_{i6}	bi7	b_{i8}	b_{i9}	b_{i10}	b_{i11}	b_{i12}	b_{i13}	b_{i14}	b_{i15}	b_{i16}	b_{i17}	b_{i18}	b_{i19}	b_{i20}	b_{i21}
		eng	mat	phy	bio	agr	eco	geo	che	adm	sta	tdr	com	enl	crk	frc	his	acc	pos	gov	fat	Hec
05_214	20031678	4	4	3	3	4	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0
05_300	20001411	4	4	4	4	4	4	4	4	0	0	0	0	0	0	0	0	0	0	0	0	0
05_140	200217896	2	3	2	4	0	3	4	2	0	0	4	0	0	0	0	0	0	0	0	0	0
05_907	20031970	3	2	4	3	2	2	2	2	0	2	0	0	0	0	0	0	0	0	0	0	0
05_567	20011400	4	4	4	4	0	0	3	0	1	4	0	0	0	0	0	0	0	0	0	0	0
05_696	20031689	3	2	0	1	3	4	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0
05_1254	2002133	2	3	4	3	4	2	4	4	4	0	0	0	0	0	0	0	0	0	0	0	0
05_1915	2003177	2	4	2	1	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0
05_700	200311999	2	4	3	4	3	1	0	4	0	0	2	0	0	0	0	0	0	0	0	0	0
05_2345	20001786	1	4	2	1	4	0	0	1	2	0	0	0	0	0	0	0	0	0	0	0	0
05_117	1999154	2	3	4	4	4	4	0	4	3	0	0	0	0	0	0	0	0	0	0	0	0
05_1100	2003177	4	4	4	3	3	2	2	3	0	0	0	0	0	0	0	0	0	0	0	0	0
05_980	2003144	2	4	4	3	4	2	2	3	0	0	0	0	0	0	0	0	0	0	0	0	0
05_115	1996120	2	4	3	0	4	4	4	3	4	0	0	0	0	0	0	0	0	0	0	0	0
05_209	1997160	4	4	3	2	4	1	4	4	0	0	0	0	0	0	0	0	0	0	0	0	0
05_7100	20021101	4	4	4	4	0	0	3	0	1	4	0	0	0	0	0	0	0	0	0	0	0
05_7214	19991167	2	4	4	3	4	2	2	3	0	0	0	0	0	0	0	0	0	0	0	0	0
05_3000	1988111	2	4	3	0	4	4	4	3	4	0	0	0	0	0	0	0	0	0	0	0	0
05_249	2000167	3	2	4	3	2	2	2	2	0	2	0	0	0	0	0	0	0	0	0	0	0
05_9000	2002115	2	4	4	3	4	2	2	3	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 6: Admission Results Table

STD_JNO	course_code	Jscore	Scut_off	Admi	ADMREM	Plcmt	PLMREM	final course
05_214	CSC	220	1	1	am			CSC
05_30	MTS	270	1	1	am			MTS
05_765	FWT	230		0	unm			
05_140	CSC	200	0	0	cnm	1	Pm	MTS
05_907	BIO	300		0	unm			
05_567	CSC	210	0	0	unm			
05_490	MTS	233	1	0	onm			
05_200	BCH	245		0	unm			
05_696	CSC	288		0	unm			
05_800	ICH	321		0	unm			
05_1254	MCB	210		0	unm			
05_915	AGP	290	1	0	onm	1	Pm	CSC
05_700	ICH	110		0	unm			
05_2345	MTS	190	0	0	cnm	0	Onm	
05_17	MTS	305		0	unm			
05_249	FWT	200		0	unm			
05_1000	CSC	245	1	1	am			CSC
05_9000	BIO	344		0	unm			
05_911	CSC	345	1	1	am			CSC
05_1010	MTS	212	1	1	am			MTS
05_1100	BCH	258		0	unm			
05_980	CSC	300	1	1	am			CSC
05_115	ICH	100		0	unm			
05_209	MCB	98	0	0	cnm			
05_715	MTS	216	1	1	am			MTS
05_2111	MTS	198	0	0	cnm	1	Pm	MET
05_7100	MTS	395	1	1	am			MTS
05_7214	FWT	288	0	0	unm			
05_3000	CSC	268	1	1	am			CSC
05_3477	BCH	279	1	1	am			BCH
05_3218	MCB	355	1	1	am			MCB
05_243	ICH	310	1	1	am			
05_915	MTS	305	1	1	am			MTS
05_616	MTS	106	0	0	unm			
05_203	FWT	133	0	0	unm			

The new system presented in this paper demonstrates that, provided all candidates' data in digital form are made available to the tertiary institutions from the various examination bodies upon certain agreements, an admission process that used to take several months due to manual processing can take just few hours, reduce every form of human processing errors, and save a lot of human hours and institutional resources. The system therefore provides a time-efficient, detailed, and unbiased automated procedure for selecting the most qualified candidates for admission into universities, ensure that candidates who fail to meet some of the admission requirements for their chosen course are automatically considered for placement into another course for which they meet the admission requirements provided there are vacant positions, and provides an avenue for candidate self-screening admission system. The manual system could not offer these aforementioned advantages.

CONCLUSION

Institutions need to keep on taking advantage of the technological advancements in the information and communications world in order to solve societal and functional problems. A successful implementation of this research has not only ensured that the most qualified candidates are offered admission into Nigerian universities, it has also provided opportunities for candidates to be automatically placed into courses (other than their chosen ones), for which they are most suited and it has also improved the level of credibility and transparency of the admission process by providing an avenue for a candidate's self-screening.

However, the following general challenges facing information and communication technologies in Nigeria have to be combated for optimum realization of the objectives of this research.

- Internet security issues: To prevent intrusion over the networks, systems must be protected from both internal and external attacks.

- Power supply problems: The current unreliable nature of the electricity supply in Nigeria calls for an alternative provision of power supplies to ensure uninterrupted service.

- Computer literacy: The level of computer literacy, particularly at the secondary school level, has to be stepped up if adequate advantage of the student's self-screening admission system is to be maximized.

Further research could be carried out to accommodate other admission requirements not considered in this study. An example readily in mind is the catchments areas (or state of origin/quota) requirements that set discriminatory cut-off marks for candidates from particular states.

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