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Visualisation of Students' Academic Performance Using Human Learning System

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Abstract **- Data miming (DM) is the technique employed in extracting relevant knowledge from data. While Educational data mining (EDM) is concerns with developing methods that will learn from the extracted knowledge that come from educational environment. The main objective of this paper is to design and develop programs and give recommendations based on the outcomes to help the University management take proactive measures on the causes of students' poor performance based on the discoveries made. We extracted seven hundred and forty-three (743) records collected from four sampled schools: School of Physical Sciences, (SPS), School of Environmental Studies (SES), School of Technology and Science Education (STSE), School of Agriculture and Agricultural Technology (SAAT) all from the Modibbo Adama University of Technology, Yola Nigeria. The Human Learning (HL) system in our model 'Framework for Evaluating Academic Performance (FEAP) to come up in our paper titled' in London Journal of Research in Computer Science and Technology, was made use of in this paper for the DM task which charts: Performance (in percentage) below/above average departmentally, Performance (in percentage) by class of degree departmentally, Performance of students (in percentage) by Mode of Entry departmentally. It made use of SQL server for the extraction of knowledge and Visual studio for charting the extracted knowledge for human visualisation. We were able to improve on how WEKA visualise data; from displaying single query charts to displaying multiple queries charts for a better performance evaluation in an inter phase that enable a user to select either WEKA GUI or HL GUI.**

Keywords: Visualisation of Students, Academic, Human Learning System, GUI, Data Mining.

I. INTRODUCTION

Educational Data Mining is concerned with developing new methods for discovering knowledge from educational database and can be used for decision making in educational system (Pal and Pal 2013). Students are the main assets of universities/Institutions. Students' good performance plays an important role in producing the best quality graduates who will become the manpower force for a country thus responsible for the country's economic development. Production of unbaked graduates from universities who will constitute the most important productive force to the society can have adverse effect on a nation's development and detrimental to lives. These graduates are also capable of replicate their breeds when employed to mentor or train the younger generations coming up.

The yardstick for majoring performance of students in higher institutions is CGPA; this index gives the overall average performance of students' examinations' grade within the time frame in the university (Clare, B et al, 2021). The main functions of data mining are applying various methods and algorithms in order to discover and extract patterns of stored data (Fayadd et al. 1996) Many factors could act as barrier or catalyst to students achieving a high CGPA that reflects their overall academic performance (Yadav et al. 2012). We have combined some of these factors with performance in our query statements, filtered and chart the outcomes so as to visualise the patterns each combination gave from the data sets mined.

The discovered knowledge can be used to offer helpful and constructive recommendations to the academic planners in higher education institutes to enhance their decision-making process, to improve students' academic performance and trim down failure rate, to better understand students' behaviour, to assist instructors, to improve teaching and many other benefits (Kumar and Chadha 2011).

II. LITERATURE

2.1 SQL

SQL stands for Structured Query Language. SQL is used to communicate with a database; it is the standard language for relational database management systems. Some common relational database management systems that use SQL are: Oracle, Sybase, Microsoft SQL Server, Access, Ingres, etc. There are no variables in SQL, everything about an SQL query must be specific – the literal values, the column names, and the table names (AbbasI, 2005).

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2.2 Distillation of Data for Human Judgment

Another area of interest within educational data mining is the distillation of data for human judgment. In some cases, human beings can make inferences about data, when it is presented appropriately, that are beyond the immediate scope of fully automated data mining methods. The methods in this area of educational data mining are information visualization methods however, the visualizations most commonly used within EDM are often different than those most often used for other information visualization problems (Hershkovitz & Nachmias, 2008), owing to the specific structure, and the meaning embedded within that structure, often present in educational data (Christopher, C. Y, et al, 2021).

2.3 User interface issues

Data mining tool become attractive when it is aesthetic, easily interpreted, and user friendly. Many data exploratory analysis tasks are significantly facilitated by the ability to see data in an appropriate visual presentation. The major issues related to user interfaces and visualization are "screen real-estate", information rendering and interaction. (Osmar and Zaïane 1999). Interaction of data and data mining tools provides hidden knowledge that can only be accessed and understood by professionals. Data entry or transformation platforms are accessed through this medium, solutions are also proffered through same.

2.4 Visualisation

Visualisation is a tool used to make results obtained represented in a graphical view for easier understanding and comprehension. It enables a user picture the Discovered knowledge from different perspectives and conceptual levels. Visualization also helps determine difficulty of the learning problem. WEKA can visualize single attributes (1-d) and pairs of attributes (2-d), rotate 3-d visualizations (Xgobi-style). WEKA has "Jitter" option to deal with nominal attributes and to detect "hidden" data points (Aksenova, 2004). WEKA also lets you to visualize classification errors.

III. METHODOLOGY

3.1 Techniques and Methods

In this work, we used the following methods and tools to help solve the problems indentified in the study;

i) Data Extraction
ii) Applying SQL Queries in order to filter hidden knowledge
iii) Using Visual Studio to plot charts on the extracted knowledge
iv) Human Learning Model

3.2 Sample of SQL Statements

The following SQL statement counts Performance Below and Above Average departmentally

```
SELECT     dbo.AB_Ave.DEPARTMENT,
           ISNULL(dbo.AB_Ave.ABOVE_AVERAGE, 0) AS
           ABOVE_AVERAGE,
           ISNULL(dbo.BL_AV.BELOW_AVERAGE, 0) AS
           BELOW_AVERAGE

FROM       dbo.AB_Ave LEFT OUTER JOIN

dbo.BL_AV ON dbo.AB_Ave.DEPARTMENT =
           dbo.BL_AV.DEPARTMENT
```

Count of Performance by Class of Degree departmentally

```
SELECT     dbo.SECOND_CLASS.DEPARMENT,
           dbo.SECOND_CLASS.FIRST_CLASS,
           dbo.SECOND_CLASS.SECOND_CLASS_UPPER,
           dbo.SECOND_CLASS.SECOND_CLASS_LOWER,

           ISNULL(dbo.THIRD_CLASS.THIRD_CLASS, 0)
           AS THIRD_CLASS,
           ISNULL(dbo.PASS_DEGREE.PASS_DEGREE, 0)
           AS PASS

FROM       dbo.PASS_DEGREE INNER JOIN

           dbo.THIRD_CLASS ON
           dbo.PASS_DEGREE.DEPARTMENT =
           dbo.THIRD_CLASS.DEPARTMENT RIGHT
           OUTER JOIN

           dbo.SECOND_CLASS ON
           dbo.THIRD_CLASS.DEPARTMENT =
           dbo.SECOND_CLASS.DEPARMENT
```

Count of Performance by Mode of Entry departmentally

```
SELECT     dbo.AboveAverage_EntryMode.DEPARTMENT,
           ISNULL(dbo.AboveAverage_EntryMode.ABOVE_A
           VERAGE_DE, 0) AS ABOVE_AVERAGE_DE,
           ISNULL(dbo.AboveAverage_EntryMode.ABOVE_A
           VERAGE_UTME, 0)

                AS ABOVE_AVERAGE_UTME,
           ISNULL(dbo.AboveAverage_EntryMode.AboveAver
           age_PreDegree, 0) AS
           ABOVE_AVERAGE_PRE_DEGREE,
           ISNULL(dbo.Below_Average_EntryMode.BELOW_
           AVERAGE_DE, 0)

                AS BELOW_AVERAGE_DE,
           ISNULL(dbo.Below_Average_EntryMode.BELOW_
           AVERAGE_UTME, 0) AS
           BELOW_AVERAGE_UTME,
```

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ISNULL(dbo.Below_Average_EntryMode.BELOW_AVERAGE_PRE_DEGREE, 0)

AS BELOW_AVEARAGE_PREE_DEGREE

FROM dbo.AboveAverage_EntryMode LEFT OUTER JOIN

dbo.Below_Average_EntryMode ON dbo.AboveAverage_EntryMode.DEPARTMENT = dbo.Below_Average_EntryMode.DEPARTMENT

Count of Performance by Gender departmentally

SELECT dbo.FEMALE_VIEW.DEPARTMENT, dbo.FEMALE_VIEW.ABOVE_AVERAGE_FEMALE, dbo.FEMALE_VIEW.BELOW_AVERAGE_FEMALE, dbo.MALE_VIEW.MALE_ABOVE_AV, dbo.MALE_VIEW.MALE_BELOW_AV

FROM dbo.FEMALE_VIEW LEFT OUTER JOIN

dbo.MALE_VIEW ON dbo.FEMALE_VIEW.DEPARTMENT = dbo.MALE_VIEW.DEPARTMENT

Count of Performance by Marital Status departmentally

SELECT dbo.MARRIED_VIEW.DEPARTMENT, dbo.MARRIED_VIEW.ABOVE_AVERAGE_MARRIED, dbo.MARRIED_VIEW.MARRIED_BELOW_AVERAGE, dbo.SINGLE_BELOW_VIEW.SINGLE_ABOVE_AVEARAGE,

dbo.SINGLE_BELOW_VIEW.SINGLE_BELOW_AVERAGE

FROM dbo.MARRIED_VIEW LEFT OUTER JOIN

dbo.SINGLE_BELOW_VIEW ON dbo.MARRIED_VIEW.DEPARTMENT = dbo.SINGLE_BELOW_VIEW.DEPARTMENT

shows the Count of Performance by Age Group departmentally

SELECT dbo.AGERANGE_1.DEPARTMENT, ISNULL(dbo.AGERANGE_1.ABOVE_AVERAGE_BELOW_20, 0) AS ABOVE_AVERAGE_AGE_BELOW_20, ISNULL(dbo.AGERANGE_1.BELOW_AVERAGE_AGE_20, 0)

AS BELOW_AVERAGE_AGE_BELOW_20, ISNULL(dbo.AGERANGE_1.ABOVE_AVERAGE_ABOVE_20_TO_30, 0) AS ABOVE_AVERAGE_AGE_20_TO_30, ISNULL(dbo.AGERANGE_1.BELOW_AVERAGE_AGE_20_TO_30,

0) AS BELOW_AVERAGE_AGE_20_TO_30, ISNULL(dbo.AGERANGE_2.ABOVE_AVERAGE_31_TO_40, 0) AS ABOVE_AVERAGE_AGE_31_TO_40, ISNULL(dbo.AGERANGE_2.BELOW_AVERAGE_31_TO_40, 0)

AS BELOW_AVERAGE_AGE_31_TO_40, ISNULL(dbo.AGERANGE_2.ABOVE_AVERAGE_AGE_41_TO_55, 0) AS ABOVE_AVERAGE_AGE_41_TO_55, ISNULL(dbo.AGERANGE_2.BELOW_AVERAGE_AGE_41_TO_55, 0)

AS BELOW_AVERAGE_AGE_41_TO_55

FROM dbo.AGERANGE_1 LEFT OUTER JOIN

dbo.AGERANGE_2 ON dbo.AGERANGE_1.DEPARTMENT = dbo.AGERANGE_2.DEPARTMENT

FIRST CLASS

SELECT DEPARTMENT, IS NULL(COUNT(CGPA), 0) AS FIRST_CLASS

FROM dbo.Student_Infor_Tbl

WHERE (CGPA = 'GREATER THAN 4.49')

GROUP BY DEPARTMENT

3.3 Human Learning (HL) Model

HL is the aspect that is concern with dissemination of informed practice trough various thresholds in SQL. This information can be useful to an individual, committee or management through algorithms that will output results in a visual form.

Parameter queries are written for end users to run. At runtime, the end user is asked to provide specific values for all the variables, like the Faculty, Department and programme. These values are placed in the GUI layer, before the SQL query is sent to the DBMS engine for processing. SQL Parameter query was used in order to make the software

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interactive and user friendly, meeting the users' needs instead of rigid query statements that might not meet a particular demand of a user. What has been extracted has been further charted using Visual studio.

3.4 Performance

The word performance was used in naming one of the attributes used in the data set as detailed in table 1 below.

Table 1: CGPA further compressed into two instances

CGPA	PERFORMANCE
Above 2.39	Yes
Below 2.40	No

IV. DISCUSSION OF RESULTS

The HL model results have developed using the extracted data that meet specified criteria. The results in the table were the computed percentage of each data item.

Table 2: Performance of Students (in percentage) below and above average, departmentally

DEPARTMENT	PERFORMANCE NO	PERFORMANCE YES
Food science and technology	24	76
Architecture	17	83
Geography	42	58
Industrial Design	36	64
Survey and geo-informatics	33	67
Urban Regional Planning	23	77
Computer Science	14	86
Mathematics	19	81
Physics	0	100
STAT/OR	28	72
Science Education	11	89
Technology Education	21	79
Vocational Education	23	77

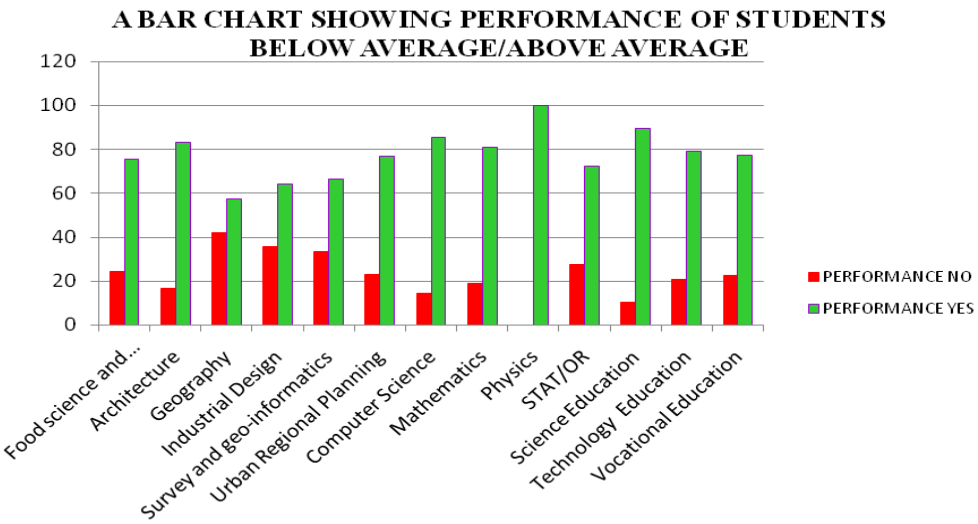

Figure 1: Performance (in percentage) below/above average departmentally

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4.1 Results Discussion of Figure 1

The chart in figure 1 above shows that student's performance is commendable except for departments like Geography, Industrial Design, Survey and STAT/OR which need further investigations as to why a large number of students performed below average.

Table 3: Count of Performance by Class of Degree departmentally

DEPARTMENT	1st Class	2nd Class Upper	2nd Class Lower	Third Class	Pass Degree
Food science and technology	-	21	58	18	3
Architecture	4	19	61	11	4
Geography	-	15	44	25	15
Industrial Design	-	13	51	29	7
Survey and geo-informatics	4	18	44	31	3
Urban Regional Planning	4	27	46	21	2
Computer Science	3	32	53	11	1
Mathematics	4	43	34	15	4
Physics	-	20	30	50	-
STAT/OR	3	23	42	23	10
Science Education	4	37	49	9	1
Technology Education	-	17	59	21	3
Vocational Education	-	27	50	23	-

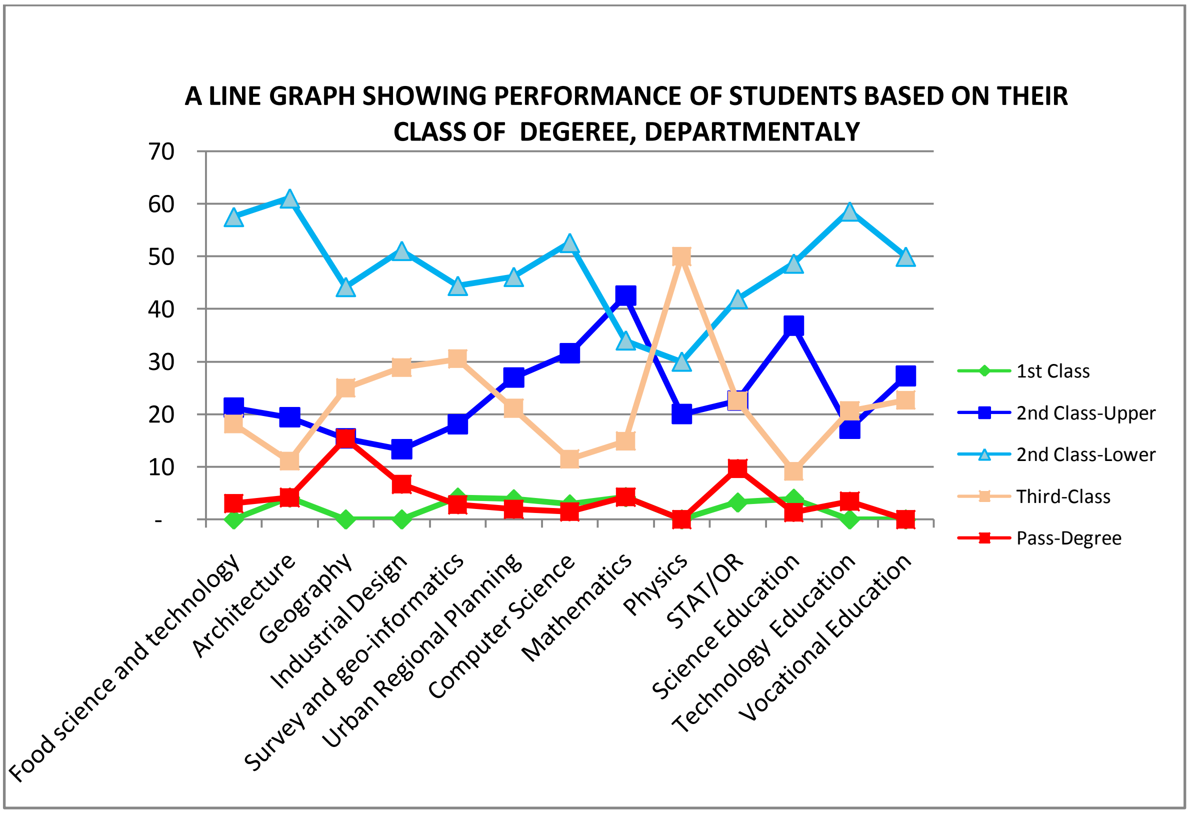

Figure 2: Performance (in percentage) by class of degree departmentally

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4.2 Results Discussion of Figure 2

The chart on figure 2 Shows that first class and Pass degree are on the lowest side in all departments; though pass degree seem to be a bit higher in Geography and STAT/OR departments. There are more students that are in the second class lower than any other class except for departments like Mathematics and Physics that their highest population in the Second Class Upper and Third Class respective. There is low occurrence of third class in Architecture, Computer science, Mathematics, Physics and Science education. Survey, Urban and regional planning, Computer science, Physics, and Science education have more number of students with pass degree.

Table 4: Count of Performance by Mode of Entry departmentally

Department	DE Performance= No	pre-degree Performance= No	UTME Performance= No	DE Performance= Yes	Pre-Degree Performance= Yes	UTME Performance= Yes
Food science and technology	6	0	18	30	0	45
Architecture	1	1	14	19	3	61
Geography	6	0	37	12	2	44
Industrial Design	4	0	31	9	4	51
Survey and geo-informatics	6	3	25	8	0	58
Urban Regional Planning	0	2	21	13	2	62
Computer Science	4	0	10	29	2	55
Mathematics	4	0	15	26	2	53
Physics	0	0	0	60	0	40
STAT/OR	17	0	10	34	0	38
Science Education	4	0	7	57	0	33
Technology Education	7	0	14	66	0	14
Vocational Education	14	0	9	55	0	23

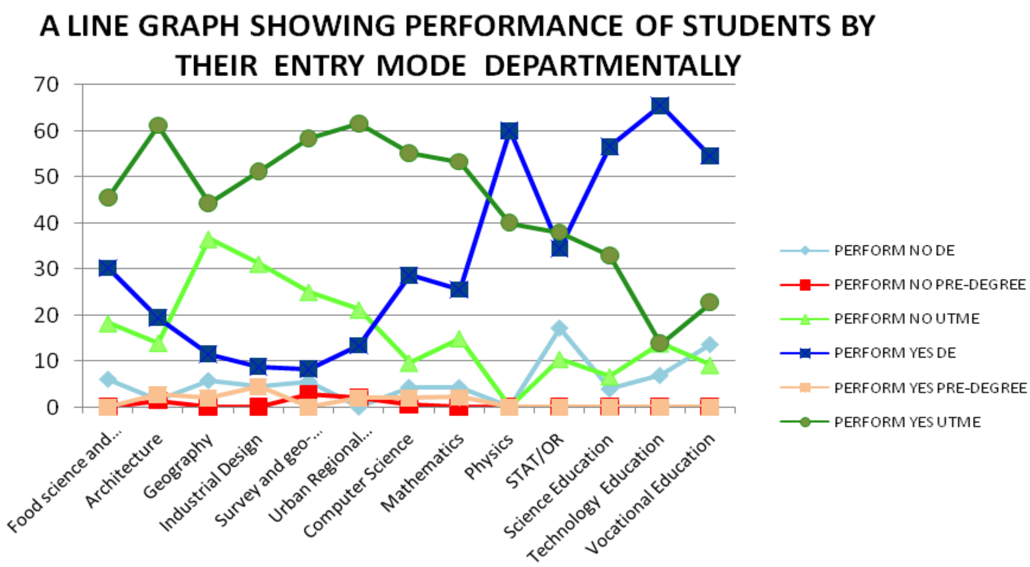

Figure 3: Performance of students (in percentage) by Mode of Entry departmentally

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4.3 Results Discussion of Figure 3

The figure 4 above shows that students who came through UTME entry have the overall best performance except for Physics and the three educational courses: Science Education, Technology Education and Vocational Education where students who came in through DE outperformed those that came in through other entries. Predegree entry performance is very low; the only two departments that show little evidence of performance are Architecture and Industrial Design.

V. CONCLUSION

We were able to show that an efficient Human Learning data mining models is achievable using complex queries that combines performance and other factors that might be of interest to a researcher in order to uncover hidden knowledge that was in a database. The model FEAP demonstrates some of the outcomes of the human learning systems using charts. One of our discoveries in figure 3 is that students that gain entry into the University through UTME i.e. straight from secondary school, perform better than those that took diploma programmes or pre-degree before proceeding to the University. We also discover that National Colleges of Education (NCE) prepare students better for University take off than diploma programmes; though the set back of this could be attributed to the fact that Universities offer diploma programmes that are not well articulated and coordinated. In our future work we shall compare performance of students who gained admissions through University diplomas with those through Polytechnics.

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