The Strength of Agreement of Students' Academic Performances as A Counseling Guide for The University Prospective Admission Seekers

Oluwafemi Samson BALOGUN* and Mazhar MOHSIN

School of Computing, University of Eastern Finland, Kuopio, Finland, samson.balogun@uef.fi* and mazhar.mohsin@uef.fi

Sunday Adewale OLALEYE
Department of Marketing, Management and International Business, Oulu Business School, Erikki-Koiso-Kanttilan, Oulu 90570, Finland, sunday.olaleye@oulu.fi

Abstract

This research examines the strength of agreement of students' academic performances for their first and graduating year in the University using Cohen's kappa. Academic records of 710 students which consist of students Grade Point Average (GPA) and Cumulative Grade Point Average (CGPA) for their first and graduating year. This paper is to examine the final academic performances of students in the University based on specific information regarding their academic performances during their first year at the University. This study reveals that a strong agreement exists between the students' first and graduating year academic performance in their result. This work will serve as a useful counseling guide to prospective admission seekers and all stakeholders at enhancing students' academic performances in the University system. This study is divided into five sections: introduction, literature, methodology, discussion while the study limitation and future study forms the part of the conclusion.

Keywords: Academic performance, Intra-class kappa, Cohen's kappa, Cumulative grade point average

Introduction

Academic performance is the outcome of student-teacher efforts, and it depicts the student's preparation and how well the students respond to the material presented to them in the class by the teacher. Research on academic performance is growing, and many authors have contributed positively to the research domain of academic performance, theoretically and methodologically. Some of the recent studies by (Mensink and King, 2020) focused on student online feedback based on the assessment marks, gender and academic performance with educational data mining and discovered gender divergence in how students get feedback through the Learning Management Systems (LMS).
Besides, (Baert et al., 2020) explore the correlation or causal relationship of Smartphone use and academic performance with samples from two Belgian Universities with instrumental variable estimation techniques, and their results show that a standard-deviation increase in daily use of Smartphone by the students yields a decrease in their average examination scores. (Donovan et al., 2020) digressed to the environmental impact on student's academic performance based on individual-level standardized mathematics and reading test scores.

They found that an I-SD upward shift in road density within 100 m of a student's home associates with advancing from the 50th percentile to the 47th percentile on reading tests. Consistent with (Mensink and King, 2020) study, (Fernandes et al., 2019) also used data mining to predict the academic performance of students in the central part of Brazil within school terms of two years, and their study found that the attributes of student grades and absences are the most relevant variables to predict the year academic outcomes of student performance. Recent studies by (HemaMalini, Suresh and Kushal,

2020) applied three machine learning techniques for performance analysis of the students and determined the factors affecting their performance. The result shows that Random Forest is the best technique in terms of accuracy, and the factors that contribute to student's performance are parent's education, attention from the faculty members to perform better, number of backlogs, and admission quota while (Mallikarjun Rao and Ramana Murthy, 2020) predicted and examined factors affecting student's performance using the XGBoost classifier.

The result identified parent education, the medium of instruction, style of learning as some of the factors that influence students' performance. (Yaacob et al., 2019) also used supervised data mining to predict student performance using some selected universities in Malaysia. The result shows that Naive Bayes performed better than the other methods. It also reveals some factors contributing to the students' performance. The authors focused on students' performance in different perspectives with different data analysis techniques but the aspect of strength of agreement of students' academic performances as a counseling guide for the University prospective admission seekers is insufficiently researched.

This research, therefore, considers the influences of the student's academic performances during their first year in the University and on their final academic performances and the main objective of this paper is to examine the final academic performances of students in the University based on specific information regarding their academic performances at their first year in the University. Results from this study would enable students to efficiently prioritize their social engagements vis-à-vis their academic activities during their first year in the University as build-up steps towards attaining academic excellence at the end of their studies at the University. This study is divided into five sections: introduction, literature, methodology, discussion while the study limitation and future study forms the part of the conclusion.

Exegesis of Performance Literature

Research is progressive in the research domain of students' academic performance and several researchers have examined the phenomenon. For instance, (Sadiq and Ahmed, 2019) classified and predicted student's performance using Decision Tree C4.5, Random Forest, Support Vector Machine, and Naïve Bayes. The authors also came up with an improved Decision Tree and compared it with the traditional Decision Tree C4.5. The result shows that the improved Decision Tree performed better than the traditional one when applied to three Universities in Iraq. (Sawant et al., 2019) employed Decision Tree in predicting student's performance by including some other factors that may affect their performance in the dataset used.

Still on the use of Decision Tree, (Adebayo and Chaubey, 2019) employed it in classifying and predicting student's performance in high school during a quiz. The authors reveal that the result will help teachers and students predict future performance based on the previous score in the quiz. Moreso, (Sitepu et al., 2019) compared the performance of the Decision Tree and Support Vector Machine method in classifying and predicting the student's performance in getting a scholarship. The result reveals that Decision Tree outperformed the Support Vector machine method in terms of accuracy to predict student's performance in getting a scholarship.

Differentiating from Decision Tree, (Alkadhwi and Adebayo, 2019) used the K-means algorithm to predict the student's performance. The authors reveal that the information from the result can be used by the Universities and Education sector to prevent drawbacks and failures in student's results in the future while (Salal, Abdullaev and Kumar, 2019) implemented nine algorithms to predict and classify the student's performance. The result shows that the school and the study time of the students play a significant role in affecting the student's performance, and three algorithms performed better in terms of accuracy in predicting the students' performance.

Besides, (Sasikala, Rajesh and Sreevidya, 2020) classified and predicted the academic performance of Alcoholic students using a classification model that uses Naïve Bayes and ID3. The authors compared the accuracy of R and Weka in terms of Naïve Bayes. The result shows that Naïve Bayes implemented in R performs better in terms of accuracy than Weka. The accuracy is the same when all the attributes and some of the attributes implemented in R and Weka for ID3 and (Mavani et al., 2020) employed Naïve Bayes classification, which is implemented in R, Weka, Python, and Orange to predict student's performance in S.S.C. and H.S.C. examinations. The result reveals that the Naïve Bayes implemented in Weka performs better in terms of accuracy. The authors suggest that future work will be able to identify the student that needs special attention and guidance to increase their likelihood placement.

Machine learning is now a groundbreaking data analysis technique and (Sana, Siddiqui and Arain, 2019) employed three different classifiers such as Naive Bayes, Decision Tree, and Artificial Neural Network, to examine the effect of some factors on student's performance. In terms of accuracy the result reveals that Artificial Neural Network is the best. Also, the result shows that student's punctuality and parents participating in the learning process are some of the factors that influence students' performance.

Also, (Adejo and Connolly, 2018) predicted student academic performance using multi-data sources with a multi-model different ensemble approach and founds that the approach used command efficiency and accuracy in predicting student performance and helps to identify the student risk of attrition. Also, (de Boer et al., 2018) carried out a meta-analysis review of the effects of metacognitive strategy instruction on student academic performance. Their study discovers the positive small increase effects of long-term strategy, but some specific strategies employed such as metacognitive, cognitive, management, and motivation failed to moderate the overall positive long-term effect of metacognitive strategy instruction. All the studies mentioned above show that one data analysis technique is not sufficient to evaluate and predict student academic performance. Applied linear regression and correlation analysis characterize the study of (Balogun, Oyelere and Atsa'am, 2019) as they determine the relationship between computing students' initial and final academic performance to support decision making in higher education institutions. Their study shows that there is a strong relationship between their first GPAs and graduating CGPA.

Education is defined as an efficient technique for the exchange and change of culture, through formal or informal training of people in a society (Oghuvbu, 2007) . It is a procedure that prompts mental, physical, psychological, and social development of a person in a given society. The prime target of getting educated throughout the world geared towards labor improvement that would encourage national development and advancement. As an instrument for the advancement of man and the general public, the way towards acquiring formal education can be compartmentalized into different categorized stages starting from primary (kindergarten) to higher (tertiary) levels (Ebong, 1996). This various categorized structure of education varies, starting with one nation then onto the next. Presently, there are 165 government-endorsed Universities in Nigeria, 43 of which built up and supported by the Federal Government of Nigeria, and the State Governments own 47 in Nigeria while private entities also own 43. These universities admit several students into their various programs and graduated a reasonable number of them with a different class of degrees annually.

The employability of graduates after University, to a great extent, relies upon the class of degrees they had at the end of their programme. Consequently, it is essential to analyze and assess the procedures that decide the final academic performances of the students while they are still in the Universities. The first year of students in the University is usually portrayed by a long list of activities such as orientation programme, students' union activities, traveling show, having sideshows, sightseeing and rides, engaging in games of skill and the like, all in a bid to get themselves adapt to the new school environment not quite the same as their origination. While these activities would enhance the social status of the students in the school, regrettably, they are similarly equipped for diverting the students from their genuine academic pursuit for their admission into the school.

Cohen's kappa coefficient (k) is a statistic that uses to measure inter-rater reliability (and intra-rater reliability) for qualitative (categorical) items. Kappa statistic is an excellent tool to test the level of agreement between two raters. Relevant studies such as (Banjoko et al., 2015) used kappa statistics to examine the strength of agreement between students' academic performance after their first and graduating year and also examine the factors that influence the students' academic performances at graduation by fitting a Multiple regression model. Also, (Elepo and Balogun, 2016) used Cohen's kappa and Intra-class kappa statistics to examine students' academic performance using their GPA and CGPA in their first and final year.

There are similarities in student's performance studies. (Oguntunde et al., 2018) and (Popoola et al., 2018) used comparable data in their work to study the trend of students' performance in the tertiary institution using multiple regression and correlation analysis for the students first, second, third, fourth-year GPA and final CGPA. They found out there is a strong relationship between the students' GPA and their CGPA. In the current study, we will be using Kappa statistics to reveal the strong agreement that exists between the students' first and graduating year academic performance. The study also shows the percentage of students who improve, maintained, or drop in their academic performance using the same dataset.

Material and Methods

Data Description: Data on results of academic performances of programs in three engineering departments (Information communication engineering, Mechanical engineering, and Petroleum engineering department), Covenant University, Nigeria, during the 2005/2006 academic session were followed-up to their year of graduation in 2010. The academic performance of the students in various courses offered in a session recorded in percentage scores with possible marks obtainable by the student ranged from 0% to 100%. We convert these percentage scores to weighted grade point (WGP), which were after that converted to grade point average (the term used for student's academic performance point average, the term used for student's academic performance point at the end of their second year and beyond in the university).

At the end of the session, the class of degree of a student determines the GPA or CGPA point obtained. Also, the performance of students during the first session of the programme recorded as the GPA, which is a function of courses' credit units and grade points. For two or more sessions, the performance of the student recorded as the CGPA. The dispersion of the scope of GPA or CGPA points attainable by students and their respective classes of degree as appropriate by National University Commission (NUC), the body is responsible for the regulation of University education in Nigeria, as presented in Table 1. Any student that produces a GPA or CGPA point between 0.00 and 0.99 would be withdrawn from the programme or placed on probation (repeat the academic level) depending on whether the student is in their first year or second year and higher of his/her academic programme respectively.

Table 1: Table of possible GPAs or CGPAs

Obtainable GPA or CGPA	Class of degree
$4.50 - 5.00$	First class (honours) -1st Class
$3.50 - 4.49$	Second class (honours) upper division – 2nd class upper
$2.40 - 3.49$	Second class (honours) lower division – 2nd class lower
$1.50 - 2.39$	Third class (honours) – 3rd class
$1.00 - 1.49$	Pass
$0.00 - 0.99$	Fail

Methodology

To set up an agreement between the initial classes of degrees of students at the end of their first year in the university estimated by their GPAs and final class of degrees they attained at the end of their study equally estimated by their CGPAs, a measure of agreement using Cohen's kappa and intra-class kappa statistic (Scott, 1955; Banerjee et al., 1999; Lawal, 2003; Dou et al., 2007; Bloch and Kraemer, 1989). Cohen's Kappa statistic is a correlation-like coefficient that measures the pairwise agreement between two raters in order to decide whether the observed agreement attained by chance or not (Donner and Eliasziw, 1992). (Fleiss, Cohen and Everitt, 1969) extended this idea to come up with a weighted Kappa statistic to evaluate the ordinal scale degrees of agreement or disagreement.

By and large, two possible uses of kappa are (i) to test raters' independence, that is, as a test statistic for testing the null hypothesis that there is no agreement between the two raters than might occur by chance given random guessing and (ii) to quantify the level of agreement (effect-size measure), which is of more worry in this work.

For any typical square $r \times c$ contingency table (with $r = c$) as given by Table 2 ($for\ r = c = 5$), the Kappa statistic k_a definition is:

$$k_a = \frac{(\pi_0 - \pi_e)}{(1 - \pi_e)} \tag{1}$$

$$\text{Where; } \pi_0 = \sum_{i=1}^{r} \pi_{ii} \text{ with } \pi_{ii} = \frac{n_{ii}}{n_{..}};\ \pi_e = \pi_{i.}\pi_{.j} = \frac{1}{n_{..}^2}\sum_{i=1}^{r}\sum_{j=1}^{r}\frac{n_{i.} \times n_{.j}}{n_{..}} \tag{2}$$

The Intra-class Kappa defines as data comprising of blind dichotomous ratings on each of n subjects by two fixed raters. The presumption that the ratings on a subject are interchangeable that is, in the population of subjects; the two ratings for each subject have a distribution that is invariant under permutations of the raters to guarantee that there is no rater bias (Donner and Eliasziw, 1992; Bloch and Kraemer, 1989; Scott, 1955). The Intra-class Kappa k_i defined as:

$$\frac{(\pi_0^* - \pi_e^*)}{(1 - \pi_e^*)} \tag{3}$$

$$\text{Where } \pi_0^* = \sum_{i=1}^{r} n_{ii} \text{ and } \pi_e^* = \sum \left[\frac{n_{i.} + n_{.j}}{n_{..}} \Big/ 2 \right]^2 \tag{4}$$

Table 2: A typical 5 × 5 contingency table used for computation of Cohen's Kappa and Intra-class Kappa coefficients and for raters agreement between two independent raters

Class of Degree		**Final Class of Degree (j)**					**Total**
		1st	**2¹**	**2²**	**3rd**	**Pass**	
Initial Class of Degree (i)	**1st**	(n_{11})	(n_{12})	(n_{13})	(n_{14})	(n_{15})	$(n_{1.})$
	2¹	(n_{21})	(n_{22})	(n_{23})	(n_{24})	(n_{25})	$(n_{2.})$
	2²	(n_{31})	(n_{32})	(n_{33})	(n_{34})	(n_{35})	$(n_{3.})$
	3rd	(n_{41})	(n_{42})	(n_{43})	(n_{44})	(n_{45})	$(n_{4.})$
	Pass	(n_{51})	(n_{52})	(n_{53})	(n_{54})	(n_{55})	$(n_{5.})$
Total		$(n_{.1})$	$(n_{.2})$	$(n_{.3})$	$(n_{.4})$	$(n_{.5})$	$(n_{..})$

Table 3: Table of the interpretation of the estimates of Cohen's Kappa k_a and Intra-class Kappa k_i statistic

Interval of Kappa Estimate	Strength of agreement
< 0.00	Poor
$0.01 - 0.20$	Slight
$0.21 - 0.40$	Fair
$0.41 - 0.60$	Moderate
$0.61 - 0.80$	Substantial
$0.81 - 1.00$	Almost perfect

There is a diverse opinion of scholars' interpretations concerning the right level of agreement using the computed Cohen's Kappa statistic k_a. Traditionally, values of k_a between $-1\ and + 1$ are used to interpret the inter-rater reliability agreement between two raters (McHugh, 2012). However, interpretations of values k_a between 0 and 1 have been a common choice in the literature (Altman, 1991; Viera and Garrett, 2005). Relatedly, Table 3 presents the interpretations of values of k_a as reported by (Altman, 1991; Viera and Garrett, 2005) for values of $k_a = 0.00$ and 1.00 indicate poor agreement and perfect agreement, respectively.

Finally, based on the observed counts in the contingency Table 2, this study determines the proportions of students that:

P_1 = the proportion of students that maintained what they started with, that is, the diagonal entries
P_2 = the proportion of students that improved on their performance, that is, those below the diagonal entries
P_3 = the proportion of students that dropped from the class of grade point they started with, that is, those above the diagonal entries from table 2 using the formula as follows:

$P_1 = \frac{1}{n_{..}} \sum_{i=1}^{4} \sum_{j=1}^{5} n_{ij}$, for $i < j$, $i = 1,2,3,4; j = 1,2,3,4,5$
$P_2 = \frac{1}{n_{..}} \sum_{i=1}^{5} \sum_{j=1}^{5} n_{ij}$, for $i = j$, $i = 1,2,3,4,5; j = 1,2,3,4,5$
$P_3 = \frac{1}{n_{..}} \sum_{i=1}^{5} \sum_{j=1}^{4} n_{ij}$, for $i > j$, $i = 1,2,3,4,5; j = 1,2,3,4$

Thus, P_1, P_2, P_3 are computed by taking the sum counts above the diagonal entries, along with the main diagonal entries, and below the main diagonal entries in Table 2 over the sample. This study utilized IBM SPSS 25 version and Microsoft Excel package for all the data analyses.

Analysis and Result

This study presents the analysis and result of the data collected from the three engineering departments on the students' performances at the end of their first and final academic sessions in this section. Table 4 presents the summary of the academic performances of students in the three engineering departments at the end of their first and final year in the University.

Table 4: showing the proportion of students that maintained their initial classes of degree, improved on their initial class of degree they started with and dropped from their initial class of degree

S/No	Department	p_1	p_2	p_3	Total
1	ICE	0.9943	0.002865	0.002865	1.00003~1
2	ME	0.5783	0.018072	0.4036	0.999972~1
3	PE	0.6615	0.051282	0.2872	0.999982~1

The observed numbers of the students that ended up with different classes of degrees in the three engineering department, the contingency table in Table 5-7 presents the distribution of the classes of degrees obtained by the students that graduated in the three engineering department as cross-classified by their initial classes of degree they had at the end of their first year in the University. Table 8 shows the equal report of distribution of all the 710 students in the three departments cross-classified by their initial and final classes of degrees they had at the end of their first and final years, respectively.

Table 5: Contingency table of Information Communication Engineering Department

Class of Degree		Final Class of Degree (j)					Total
		1st	2^1	2^2	3rd	Pass	
Initial Class of Degree (i)	1st	28	0	0	0	0	28
	2^1	0	149	0	0	0	149
	2^2	0	0	137	1	0	138
	3rd	0	0	1	33	0	34
	Pass	0	0	0	0	0	0
Total		28	149	138	34	0	349

Table 6: Contingency for Mechanical Engineering Department

Class of Degree		Final Class of Degree					Total
		1st	2^1	2^2	3rd	Pass	
Initial Class of Degree	1st	14	17	1	0	0	32
	2^1	0	55	44	0	0	99
	2^2	0	3	23	5	0	31
	3rd	0	0	0	4	0	4
	Pass	0	0	0	0	0	0
Total		14	75	68	9	0	166

Table 7: Contingency for Petroleum Engineering Department

Class of Degree		Final Class of Degree					Total
		1st	2^1	2^2	3rd	Pass	
Initial Class of Degree	1st	11	6	0	0	0	17
	2^1	4	80	48	0	0	132
	2^2	0	2	36	2	0	40
	3rd	0	0	3	2	0	5
	Pass	0	0	1	0	0	1
Total		15	88	88	4	0	195

Table 8: Contingency for three Department

Class of Degree		Final Class of Degree					Total
		1st	2^1	2^2	3rd	Pass	
Initial Class of Degree	1st	53	23	1	0	0	77
	2^1	4	284	92	0	0	380
	2^2	0	5	196	8	0	209
	3rd	0	0	4	39	0	43
	Pass	0	0	1	0	0	1
Total		57	312	294	47	0	710

Table 9: show the results of inter-rater agreement measure of Cohen's Kappa, Intra-class Kappa statistic and Chi-square test of the relationship between the classes of degrees obtained by students at the end of their first year and final year in the University in three engineering departments.

S/No	Department	Cohen's kappa	Intra-class kappa	Chi-square	P-value
1	ICE	0.9955	0.9955	1021.882	0.000
2	ME	0.3375	0.3151	712.740	0.000
3	PE	0.4308	0.4028	398.236	0.000

Discussion

The main objective of this paper is to examine the final academic performances of students in the University based on specific information regarding their academic performances in their first year at the University. However, this study emphasizes the possible relationship between the initial academic performances of the students at the end of their first year and measured by their GPAs and their final academic performances. Both of these converted into possible classes of degrees that are obtainable within the University system, as provided in Table 1.

Data on academic performances of students in three departments from Covenant University, Nigeria, were collected on 710 students. This study depicts a longitudinal study in which the academic progress of these 710 students followed up until graduation.

Based on the available information on all the academic performances of 710 students in all the three departments from Covenant University as detailed in Table 8. This study discovers that a total of 14 (1.97%) graduates improved on the classes of degrees they had in the first year of their study. Also, 572 (80.56%) of students maintained their classes of degrees they had in their first year till graduation, while 124 (17.46%) of the students dropped from the classes of degrees they started with in the first year of their study at graduation.

Surprisingly, of the 77 students that started with first-class in their first year, 53 (68.83%) of them maintained this class of degree while the remaining 24 (31.17%) dropped to (2^1) class at graduation. Specifically, out of a total of 380 students that had second upper (2^1) at the end of their first year in their departments, only 4 (1.05%) of them improved to first class ((1^{st})), 284 (74.74%) of them maintained this class of degree till graduation while 92 (24.21%) of them dropped to a second class lower (2^2).

Also, out of 209 students that started with second class lower $(2^2)$from their first year in the University, only 5 (2.39%) of them improved to second class upper. 196 (93.78%) of them maintained this class of degree till graduation while only 8 (3.83%) of them dropped to third class (3rd) degree status at graduation. Similarly, of the 43 students that had a third-class degree (3rd) in their first year, only 4 (9.30%) improved (the four students had (2^2) while 39 (90.70%) maintained this class of degree till graduation. Only one student started with a pass degree in their first year, and 1 (100%) improved to a second class lower.

The distribution of the classes of degrees obtained by 349, 166 and 195 students that graduated from Information Communication Engineering, Mechanical Engineering and Petroleum Engineering department respectively cross-classified by their classes of degrees they had at the end of their first and final years in the University is presented by the confusion matrices in Table 5, 6 and 7. The pattern of academic performance of students replicates for the three departments in this study, and the results are as follows:

Based on observation, the data in Table 5 for the 349 graduates of Information Communication Engineering department that just 1 (0.29%) student improved on its initial classes of degrees. Whereas

347 (99.43%) students maintained their initial classes of degrees till graduation (main diagonal entries) and while only 1 (0.29%) student dropped from its classes of degrees it started with at graduation.

To further examine the association between the initial and final classes of academic performance of students at the end of their first and final years in the University, the Kappa statistics were computed separately for all the three departments for which the data used is collected from Covenant University using the information provided in Tables 5, 6 and 7. The results of the Cohens Kappa and Intra-class Kappa agreement using statistic (1) and (3) as presented in Table 9 where reasonable agreement observed between the students' initial and final classes of degrees they had at the end of their first and final years of study in the University in all the departments. This result was supported by the results of the Chi-square test of association in which the p-values for each department were significant ($p < 0.05$).

Conclusion

This work examines the impact of the performances of students in higher institutions of learning, especially in the University, during their first year on their final academic achievement at graduation. Emphasis is more on determining the relationship between the initial GPAs and final CGPAs of students at their first and final years in the University system. The follow-up study on the performance of students from three Engineering departments, Covenant University, Nigeria, between 2005 and 2010, determines this development.

These results show that, generally, about 81% of the students in the University do maintain the classes of degrees they had in the first year of their program till graduation. Whereas, about 2% of the students improved on their first classes of degrees during their first year at graduation while only about 17% of them had their academic performances dropped from what they had during their first year.
Results from this study have provided vital information that is useful for prospective students of the University regarding the need to work hard during their first year on their academic programs since the outcome of such efforts would greatly determine their final academic performance on graduation from the University.

Besides, the different results from this work would serve as useful counseling resources to stakeholders in the education sector within and outside the University system towards improving the academic performances of students in the system. This study would equally benefit the parents and guardians to be able to put in place necessary measures that would assist in improving the academic performances of their children and wards in the University.

Information Communication Engineering department had the highest number of students that maintained their grade point, Petroleum Engineering department had the highest number of students who improved on their performance, and Mechanical Engineering department had the number of students that dropped. Also, the strength of agreement that exists between the first year and their final grade of the students is on the average is fair. This study is limited by secondary data and the future research should employ big data with machine learning to advance the results of this study.

Definition of terms

NUC Nigerian University Commission
GPA Grade Point Average
CGPA Cumulative Grade Point Average
ICE Information Communication Engineering Department
ME Mechanical Engineering Department
PE Petroleum Engineering Department

References

- Adebayo, A.O. and Chaubey, M.S. (2019) '*Data Mining Classification Techniques on the Analysis of Student's Performance.*', 7(4), p. 18.
- Adejo, O.W. and Connolly, T. (2018) 'Predicting student academic performance using multi-model heterogeneous ensemble approach', *Journal of Applied Research in Higher Education*, 10(1) Emerald Publishing Limited, pp. 61–75.
- Alkadhwi, A. H. O. and Adebayo, A. O. (2019). 'Data mining application using Clustering techniques (K-means Algorithm) in the analysis of student's performance'. *Journal of Multidisciplinary Engineering Science Studies*, 5(5), pp. 2587-2593.
- Altman, D. G. (1991) 'Practical Statistics for Medical Research'. London England: Chapman and Hall.
- Baert, S., Vujić, S., Amez, S., Claeskens, M., Daman, T., Maeckelberghe, A., Omey, E. and Marez, L.D. (2020) 'Smartphone Use and Academic Performance: Correlation or Causal Relationship?', *Kyklos*, 73(1), pp. 22–46.
- Balogun, O.S., Oyelere, S.S. and Atsa'am, D.D. (2019) 'Data analytics on performance of computing students', *Proceedings of the 19th Koli Calling International Conference on Computing Education Research*. Koli, Finland: Association for Computing Machinery. Koli Calling '19, pp. 1–2. Available at: 10.1145/3364510.3366152 (Accessed: 16 May 2020).
- Banerjee, M., Capozzoli, M., McSweeney, L. and Sinha, D. (1999) 'Beyond Kappa: A Review of Interrater Agreement Measures', *The Canadian Journal of Statistics / La Revue Canadienne de Statistique*, 27(1) [Statistical Society of Canada, Wiley], pp. 3–23.
- Banjoko, A. W., Yahya, W. B., Abiodun, H. B., Adeleke, M. O., Afolayan, R. B., Garba, M. K., Olorede, K. O. and Dauda, K. A. (2015). 'On the strength of agreement between students' initial and final academic performances in Nigeria University System'. *Nigeria Journal of Mathematics and applications*, 24, pp. 137-156.
- Bloch, D.A. and Kraemer, H.C. (1989) '2 x 2 Kappa Coefficients: Measures of Agreement or Association', *Biometrics*, 45(1) [Wiley, International Biometric Society], pp. 269–287.
- de Boer, H., Donker, A.S., Kostons, D.D.N.M. and van der Werf, G.P.C. (2018) 'Long-term effects of metacognitive strategy instruction on student academic performance: A meta-analysis', *Educational Research Review*, 24, pp. 98–115.
- Donner, A. and Eliasziw, M. (1992) 'A goodness-of-fit approach to inference procedures for the kappa statistic: Confidence interval construction, significance-testing and sample size estimation', *Statistics in Medicine*, 11(11), pp. 1511–1519.
- Donovan, G.H., Michael, Y.L., Gatziolis, D. and Hoyer, R.W. (2020) 'The Relationship Between the Natural Environment and Individual-Level Academic Performance in Portland, Oregon', *Environment and Behavior*, 52(2) SAGE Publications Inc, pp. 164–186.
- Dou, W., Ren, Y., Wu, Q., Ruan, S., Chen, Y., Bloyet, D. and Constans, J.-M. (2007) 'Fuzzy kappa for the agreement measure of fuzzy classifications', *Neurocomputing*, 70(4), pp. 726–734.
- Elepo, T.A. and Balogun, O.S. (2016) 'Statistical Analysis on Students' Performance', *Covenant Journal of Informatics and Communication Technology*, 4(1) Available at: http://journals.covenantuniversity.edu.ng/index.php/cjict/article/view/217 (Accessed: 14 May 2020).
- Ebong, E. 1996. "Early Childhood Education: Concept and Scope", (pp. 7-20), O. I. Obinaju (ed.), Early Childhood Education Theory and Practice. Calabar: Bow Universal Ltd.
- Fernandes, E., Holanda, M., Victorino, M., Borges, V., Carvalho, R. and Erven, G.V. (2019) 'Educational data mining: Predictive analysis of academic performance of public school students in the capital of Brazil', *Journal of Business Research*, 94, pp. 335–343.
- Fleiss, J.L., Cohen, J. and Everitt, B.S. (1969) 'Large sample standard errors of kappa and weighted kappa', *Psychological Bulletin*, 72(5) US: American Psychological Association, pp. 323–327.
- HemaMalini, B.H., Suresh, L. and Kushal, M. (2020) 'Comprehensive Analysis of Students' Performance by Applying Machine Learning Techniques', Satapathy, S. C., Bhateja, V., Mohanty, J. R. and Udgata, S. K. (eds.)*Smart Intelligent Computing and Applications*. Singapore: Springer. Smart Innovation, Systems and Technologies, pp. 547–556.

- Lawal, B. H. (2003): 'Categorical data analysis with SAS and SPSS applications'. Lawrence Erlbaum Associates Inc.
- Mallikarjun Rao, B. and Ramana Murthy, B.V. (2020) ‘Prediction of Student’s Educational Performance Using Machine Learning Techniques’, Raju, K. S., Senkerik, R., Lanka, S. P. and Rajagopal, V. (eds.) *Data Engineering and Communication Technology*. Singapore: Springer. Advances in Intelligent Systems and Computing, pp. 429–440.
- Mavani, U., Lobo, V.B., Pednekar, A., Pereira, N.C., Mishra, R. and Ansari, N. (2020) ‘Naïve Bayes Classification on Student Placement Data: A Comparative Study of Data Mining Tools’, Tuba, M., Akashe, S. and Joshi, A. (eds.)*Information and Communication Technology for Sustainable Development*. Singapore: Springer. Advances in Intelligent Systems and Computing, pp. 363–372.
- McHugh, M. L. (2012): 'Interrater reliability: the kappa statistic'. *Biochem Med (Zagreb)*, 22(3), pp. 276-282.
- Mensink, P.J. and King, K. (2020) ‘Student access of online feedback is modified by the availability of assessment marks, gender and academic performance’, *British Journal of Educational Technology*, 51(1), pp. 10–22.
- Oghuvbu, E.P. (2007) ‘Education, Poverty and Development in Nigeria: The Way Forward in the 21st Century’, *Journal of Social Sciences*, 14(1) Routledge, pp. 22–24.
- Oguntunde, P.E., Okagbue, H.I., Oguntunde, O.A., Opanuga, A.A. and Oluwatunde, S.J. (2018) ‘Analysis of the inter-relationship between students’ first year results and their final graduating grades’, *International Journal of Advanced and Applied Sciences*, 5(10), pp. 1–6.
- Popoola, S.I., Atayero, A.A., Badejo, J.A., John, T.M., Odukoya, J.A. and Omole, D.O. (2018) ‘Learning analytics for smart campus: Data on academic performances of engineering undergraduates in Nigerian private university’, *Data in Brief*, 17, pp. 76–94.
- Sadiq, M.H. and Ahmed, N.S. (2019) ‘Classifying and Predicting Students’ Performance using Improved Decision Tree C4.5 in Higher Education Institutes’, *Journal of Computer Science*, 15(9) Science Publications, pp. 1291–1306.
- Salal, Y.K., Abdullaev, S.M. and Kumar, M. (2019) ‘*Educational Data Mining: Student Performance Prediction in Academic*’, 8(4), p. 7.
- Sana, Siddiqui, I.F. and Arain, Q.A. (2019) ‘Analyzing Students’ Academic Performance through Educational Data Mining’, *3C Tecnología. Glosas de innovación aplicadas a la pyme*, pp. 402–421.
- Sasikala, T., Rajesh, M. and Sreevidya, B. (2020) ‘Prediction of Academic Performance of Alcoholic Students Using Data Mining Techniques’, Mallick, P. K., Balas, V. E., Bhoi, A. K. and Chae, G.-S. (eds.)*Cognitive Informatics and Soft Computing*. Singapore: Springer. Advances in Intelligent Systems and Computing, pp. 141–148.
- Sawant, T. U., Pol, U. R., and Patankar, P. S. (2019) ‘EDUCATIONAL DATA MINING PREDICTION MODEL USING DECISION TREE ALGORITHM’, *International Journal of Emerging Technologies and Innovative Research (www.jetir.org), ISSN:2349-5162, Vol.6, Issue 5, page no.306-313* Available at: https://www.academia.edu/39295303/EDUCATIONAL_DATA_MINING_PREDICTION_MODEL_USING_DECISION_TREE_ALGORITHM (Accessed: 14 May 2020).
- Scott, W.A. (1955) ‘Reliability of Content Analysis: The Case of Nominal Scale Coding’, *The Public Opinion Quarterly*, 19(3) [Oxford University Press, American Association for Public Opinion Research], pp. 321–325.
- Sitepu, N.B., Sawaluddin, Zarlis, M., Efendi, S. and Dhany, H.W. (2019) ‘Analysis of Decision Tree and Smooth Support Vector Machine Methods on Data Mining’, *Journal of Physics: Conference Series*, 1255, p. 012067.
- Viera, A.J. and Garrett, J.M. (2005) ‘Understanding interobserver agreement: the kappa statistic’, *Family Medicine*, 37(5), pp. 360–363.
- Yaacob, W.F.W., Nasir, S.A.M., Yaacob, W.F.W. and Sobri, N.M. (2019) ‘Supervised data mining approach for predicting student performance’, *Indonesian Journal of Electrical Engineering and Computer Science*, 16(3), p. 1584.