Modelling the Effect of Academic Performance on National Achievement Test (NAT)

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Abstract: The title of this study is Predicting the Effect of Academic Performance on the National Achievement Test Using Data Mining. Students from Central Mindanao University's Senior High School (SHS) provided the data for this study. The goal of this study is to develop a model that can predict how academic performance affects the National Achievement Test. Its specific objectives are to extract predictive features of subjects that affect the National Achievement Test (NAT), determine the effects of various academic subjects on the National Achievement Test, identify the subjects that have a strong effect on the National Achievement Test, and finally determine whether academic performance per quarter affects the National Achievement Test.

1 INTRODUCTION

One of the factors used to evaluate a student's ability is academic achievement. The evaluation of periodic grades, which is the criteria for measuring academic performance, serves as the foundation for grading all scholastic activities. The National Achievement Test (NAT) is given to Filipino students every year by the Department of Education (DepEd) to guarantee that the aim of achieving quality education is realized (Ebio, Jr., 2016). The test, according to the same source, is designed to evaluate pupils' ability in a number of topics, including Mathematics, English, Science, Filipino, and others.

According to Hand (2012), data mining is a branch of computer science in which you are bound to identify some structures in non-random samples of the population if you have large enough datasets. The art of detecting patterns in massive amounts of data is known as data mining. The most important element of data mining is that; it can be used to produce new ideas, hypotheses, and predictions from datasets in a more scientific way. Data mining, also known as Knowledge Discovery in Databases (KDD), is the field of uncovering fresh and possibly usable information from enormous amounts of data, according to Baker(2007). The major goal of educational institutions is to offer students with a high-quality educat[1]ion in order to improve their academic performance (Dabhade et al., 2021.Finding patterns in datasets of national achievement tests and student academic performance may be the ideal application of Data Mining. Educational Data Mining (EDM) is a field that uses statistical, machine learning, and data-mining (DM) algorithms to analyze various forms of educational data (Romero & Ventura, 2010). EDM is also defined as the application of data mining techniques to data sets produced from educational settings that could lead to the discovery of new information (Amazona & Hernandez, 2019)

Predicting a student's performance is crucial for assisting at-risk students and ensuring their retention, as well as offering good learning materials and experience and boosting the university's ranking and reputation (Mahmoud, 2019). The purpose of this study is to construct a predictive model to assess the effect of academic performance on the National Achievement Test. The hypothesis in this study is the effect of having greater or lower academic performance on the NAT scores. Following the development of the model, it will be used to extract predictive features of subjects that affect the National Achievement Test, determine the effects of various academic subjects on the NAT, identify the subjects that have a strong effect on the National Achievement

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Test, and finally determine if academic performance per quarter affects the National Achievement Test.

With 50 publications (42.4 percent), classification is the most widely employed technique, followed by regression with 33 papers (28 percent). Clustering (11%) and association (1.7%) were employed far less frequently, as were other approaches that were not specifically mentioned (16.9% highlighted Machine Learning/ Data Mining broadly) (López-Zambrano et al., 2021). (Regio, et al., 2021). Alyahyan and Düştegör's study, Predicting academic performance in higher education: literature review and best practices, revealed an accuracy of 89.15 percent when applying the Logistic regression model.

2 RELATED WORKS

Abu Saa (2016,) conducted research on educational data mining and student performance prediction. This study used a variety of data mining tasks to create high-performing qualitative prediction models that can reliably predict students' grades based on a training dataset. A survey was sent out to students to collect personal, social, and academic information; it was then preprocessed for data mining operations; the data mining work was started; and finally, a pattern was detected. It was discovered in this study that a student's accomplishment is not solely based on their academic efforts; there are various other factors that are equally or more important. To summarize, this study can motivate and aid universities in conducting regular data mining jobs on their students' data in order to reveal interesting results and patterns that can benefit both the institution and the students in a variety of ways.

Shahiri et al., (2015) published a review on applying data mining approaches to predict student performance. The most essential features were discovered using a prediction algorithm, and educational data mining methodologies revealed that student achievement and success might be improved more effectively and efficiently. (Sorour et al., 2015) An experiment reported a model of student academic performance predictor by evaluating student comments data as predictor factors. The current study is essentially about developing a predictive model. As a result, the research is limited to text mining approaches rather than data mining techniques.

The studies of Hamsa et al., (2016) and this one are similar in terms of predicting student academic performance, however they differ in terms of algorithm because Decision Tree and Fuzzy Genetic Algorithm were utilized. It seeks to construct a model for predicting student academic performance for Bachelor and Master Degree students in Computer Science and Electronics and Communication utilizing two categorization methods: Decision Tree and Fuzzy Genetic Algorithm.

Regio et al., (2021) provide a prediction model for participant performance, allowing them to discover the elements that best explain exam results. They used accessible data from the Ministry of Education as well as the Logistic Regression approach for this project. They can infer the student's performance with a 74 percent accuracy using the predictive model. Furthermore, because they employed a statistical model that is simple to read and implement rather than a complicated Machine Learning technique, school administrators could use the results without having a comprehensive understanding of the mining technique.

3 METHODOLOGY

The Periodic Grades dataset and the National Achievement Test dataset are the two data sources used in this investigation. All of the information was obtained in hard copy from Central Mindanao University's College of Education.

This study implements the KDD (Knowledge Discovery in Database) methodology. Figure 1 shows the specific KDD (Knowledge Discovery in Database) methodology for this study using the Logistic Regression Algorithm and Feature Selection Technique.

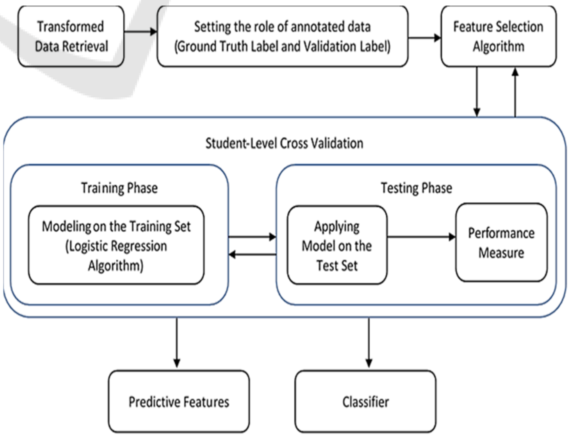

Figure 1: Logistic Regression with Feature Selection and Student-level Cross-Validation.

Periodic grades data was obtained from a total of 723 Senior High School students of Central Mindanao University when they were in grade 11 (the school year 2017-2018) and grade 12 (the school year 2018-2019) related to beginning the National Achievement Test.

The first step in preparing for the National Achievement Test dataset was to convert the hard copy to digital. The Mean Percentage Score was then categorized, and the NAT score, according to Albano (2019), follows the criteria listed in Table 1.

Table 1: National Achievement Test criteria.

NAT Scores	Criteria
0 - 35	Very Low Mastery
36 – 65	Low Mastery
66 – 85	Average Mastery
86 – 100	Moving Towards Mastery

The criteria are based on the National Achievement Test's Mean Percentage Score. Table 1 shows that the range 0–35 represents Very Low Mastery, 36–65 represents Low Mastery, 66–85 represents Average Mastery, and 86–100 represents Moving Towards Mastery. VLM is for Very Low Mastery, LM stands for Low Mastery, AM stands for Average Mastery, and MTM stands for Moving Toward Mastery.

The National Achievement Test and Periodic Grades datasets were pooled and then divided into strands. There are four strands in total: Humss, Stem, ABM, and TVL. To eliminate repetition in the attributes and data while integrating the datasets, the four files were joined using a union operator, as illustrated in Figure 2. The union operator joins multiple example sets together to form a superset. If both examplesets have a common attribute, the union operator creates a single attribute that holds the data for both sets.

4 RESULTS AND DISCUSSION

The main purpose of this study is to develop a predictive model for the National Achievement Test. In order to estimate the impact of academic success on NAT, a prediction model must be developed. The logistic regression approach was used to generate the model.

Table 2 shows the values of the model which corresponds coefficients, standard coefficients, standard error values, Wald values, P-Value which we can derive predictive value. This tables shows the variables or extracted topics represents as Var, grade level (Grade), Quarter(Quar), and predictive features Coefficient(Coeff.) , Standard Coefficient (Std. Coeff.), Standard Error (Std Err.), Wald, and subsequently the p-value).

Table 2. The Values of the Model.

Var.	Grade	Quar.	Coeff.	Std. Coeff.	Std Err.	Wald	p-value
Phy.Scie	11	4	-17.11	-9.11	7.03	-2.43	0.01
PerDev	11	2	-4.1	-15.61	1.2	-3.42	0
UCSP	11	1	-4.89	-8.07	1.91	-2.56	0.01
CLPW	12	1	-1.93	-6.71	0.9	-2.14	0.03
Philosophy	12	2	-1.36	-13.67	0.51	-2.63	0.01
EAPP	11	2	-30.97	-10.6	11.79	-2.63	0.01
Filipino	11	3	-0.65	-4.32	0.75	-0.87	0.38
MIL	12	1	-1.04	-6.06	0.58	-1.78	0.08
ELS	11	2	2.75	3.76	3.3	0.84	0.4
Filipino	11	2	0.46	3.01	0.39	1.18	0.24
EAPP	11	1	18.32	7.88	9.45	1.94	0.05
Filipino	11	4	0.15	1.24	0.69	0.22	0.82
Arts	12	2	2.7	12.95	0.57	4.73	0

Extract Predictive Features Affecting NAT. The subjects listed in Table 3, were among the 14 variables extracted by the feature selection technique used in this study; among them, there are repeated subjects that vary in quarter, so the technique selected a total of 14 variables. The assumptions of the study require these features.

Effects of Various Academic Subject in National Achievement Test. When the value of the independent variable rises, so does the mean of the dependent variable. According to the data, when the grade of the following subjects improves, the mean of the National Achievement Test rises. The feature selection algorithm clearly chose two identical subjects with positive coefficients, as shown in Table 3. Students' performance in Filipino at the same grade level and from various quarters had an unexpected impact on the National Achievement Test. It can be argued that as a student's Filipino grade rises, so does the mean of the National Achievement Test. The larger the positive correlation coefficient is in terms of its value and how it influences factors, the more likely children will score higher on the National Achievement Test. In Quarter 2, Filipino had a value of 0.46, and in Quarter 4, it had a value of.15. Quarter 2 was found to have a higher influence than Quarter 4, which only had a.15 effect.

Table 3: Positive Coefficient.

Subjects	Grade	Quarter	Coeff.
Philosophy	12	1	1.13
Filipino	11	2	0.46
Filipino	11	4	0.15
English for Academic and Professional Purposes	11	1	18.32
Earth and Life Science	11	2	2.75
Arts	12	2	2.70

The negative coefficient in Table 4 indicates that as the grades in the following topics rise, the mean of the National Achievement Test Scores falls. If the estimated coefficient is close to zero, the predictor's effect is small. When the value of a student's performance grade grows, the mean of the National Achievement Test Scores tends to fall, as seen in the table below. Among the disciplines provided are Physical Sciences, Personal Development, Understanding Culture, Society, and Politics, 21st Century Literature in the Philippines and the World, Philosophy, English for Academic Purposes, Filipino, and Media and Information Literacy.

Table 4: Negative Coefficient.

Subjects	Grade	Quarter	Coeff.
Physical Science	11	4	-17.11
Personal Development	11	2	-4.10
Understanding Culture Society and Politics	11	1	-4.89
21st Century Literature in the Philippines and the World	12	1	-1.93
Philosophy	12	2	-1.36
English for Academic and Professional Purposes	11	2	-30.97
Filipino	11	3	-0.65
Media and Information Literacy	12	1	-1.04

Strong Effect of Student Grades to the National Achievement Test. The standardized beta coefficient measures the strength of each independent and dependent variable's effect; the larger the beta coefficient's absolute value, the stronger the effect. Physical Sciences in Grade 11 from Quarters 1 and English for Academic and Professional Purposes in Grade 11 from Quarters 1 had the greatest beta coefficients, indicating a stronger linear association. The table below shows that Filipino subjects in quarters 3, 2, and 4 have the closest beta coefficient to zero, and Filipinos in the third quarter had the highest absolute beta coefficient value. This could indicate that in the National Achievement Test, this subject has a greater impact.

Academic Performance Per Quarter May Affect the National Achievement Test. Table 5 shows the results. The feature extraction algorithm chose Filipino, English for Academic and Professional Purposes, and Philosophy as subjects. Each quarter, we can only compare three subjects; the same subjects are from the same grade level and differ each quarter. Based on the coefficient value, the algorithm chose Filipino in grade 11 from quarters 3,2, and 4, English for Academic and Professional Purposes in grade 11 from quarters 2 and 1, and Philosophy in grade 12 from quarters 2 and 1.

Table 5: The same subjects extracted.

Variables	Grade	Quarter	Coeff.
Filipino	11	3	-0.65
Filipino	11	2	0.46
Filipino	11	4	0.15
English for Academic and Professional Purposes	11	2	-30.97
English for Academic and Professional Purposes	11	1	18.32
Philosophy	12	2	-1.36
Philosophy	12	1	1.13

In Quarter 3, the value of the Filipino indicates that as the value of the Filipino grows, the mean of the National Achievement Test tends to fall. On the other hand, Filipino in quarters 2 and 3 may indicate that as the grade Filipino in these quarters rises, the mean of the National Achievement Test will climb. When the grade in English for Academic and Professional Purposes in Quarter 2 of grade 11 improves, the mean of the National Achievement Test decreases. As the grade of English for Academic and Professional Purposes in Quarter 1 of grade 11 improves, the mean of the National Achievement Test will increase. When the grade of Philosophy in Quarter 2 rises, the mean of the National Achievement Test normally falls. The mean of the National Achievement Test will improve if the grade in Philosophy in Quarter 1 improves.

Validation. The VLM (Very Low Mastery) and LM (Low Mastery) anticipated values are shown in the Confusion Matrix (Low Mastery). As indicated in Table 6, 42.85% of the population received a National Achievement Test rating of Very Low Mastery, with a yield sensitivity of 96.33 percent and a fair kappa rating of.852.

Table 6: Confusion Matrix.

Observed Y	Predicted Y		Accuracy
	VLM True	LM True	
VLM True	42.85	0.26%	96.33%
LM False	7.15	49.74	87.12
Overall Accuracy			92.59%

5 CONCLUSION AND RECOMMENDATION TO FUTURE WORK

We discovered ten subjects that had a significant finding on the National Achievement Test when creating the model. Physical Science, Personal Development, Culture, Society, and Politics, 21st Century Literature in the Philippines and the World, Philosophy, English for Academic and Professional Purposes, Filipino, Media and Information Literacy, Earth and Life Sciences, and Arts are among the subjects covered.

We can deduce that not only the subjects differ, but also the quarters in which the subject was taken may have an impact on the National Achievement Test score. Students' performance in Filipino at the same grade level and from various quarters had an unexpected impact on the National Achievement Test. It can be argued that as a student's Filipino grade rises, so does the mean of the National Achievement Test. In comparison to Filipinos in Quarter 4, Filipinos in Quarter 2 have a bigger impact.

The mean of the National Achievement Test Scores tends to decrease as the value of the students' performance grade in Physical Sciences, Personal Development, Understanding Culture, Society, and Politics, 21st Century Literature in the Philippines and the World, Philosophy, English for Academic Purposes, Filipino, and Media and Information Literacy rises. Filipino subjects from quarters 3,2, and 4 have a stronger effect in the National Achievement Test.

According to the algorithm, the only three disciplines with the same quarter may have a significant impact on the National Achievement Test are Filipino, English for Academic Purposes, and Philosophy. We can presume that quarterly grades or academic achievement in the listed areas may have an impact on the National Achievement Test outcome because the coefficients for these topics vary each quarter.

The researcher may suggest studying broader datasets and including scores from other schools, such as one division or region. Another study including the use of several algorithms and comparing the results of various algorithms could yield positive results.

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