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Modeling the Performance of Senior High School Students' National Achievement Test Performance in Central Mindanao University

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ABSTRACT

The study is entitled Modeling the Performance of Senior High School Students' National Achievement Test Performance in Central Mindanao University. It aims to develop a predictive model of the National Achievement Test performance of Senior High School students. The study intends to extract predictive features of students' National Achievement Test performance, find the extent of the relationship between the students' academic performance in the previous and current year to their National Achievement Test performance, and recommend pedagogical interventions concerning National Achievement Test performance's predictive features. There were two types of datasets, National Achievement Test and Periodic grades of batch 2017 – 2018 when they were in Grade 11 and Grade 12 before taking the National Achievement Test. After the data is collected, the Feature selection and Logistic regression model is applied using the data mining process's rapid miner application. Out of 30 attributes, there are only 14 subjects selected by the feature selection technique. The feature selection selected those subjects which contributed to the prediction. We found out that Philosophy and Arts in the Last Quarter and Semester before the National Achievement Test exam has the most significant effect on the National Achievement Test Result. This study was based on a CMU-funded research entitled Leveraging Educational Data Mining and Machine Learning Techniques in Developing Strategic Interventions for Senior High School Students.

Keywords: EDM, Logistic Regression, Student Performance, Modeling

INTRODUCTION

Data Mining (DM) is a field in Computer Science that is concerned with finding patterns from large amounts of data or the discovery of properties of data through the use of various algorithms and computing tools for data exploration, visualization, and presentation in a simplified manner in order to support decisions through classification, prediction, finding clusters, relationships, and associations (Looi et al., 2005)

There are many approaches to learn patterns and properties from data, and one popular approach is using Machine Learning (ML) techniques (Witten et al., 2016). Using both DM and ML methodologies, scholars have started to investigate how these can improve educational research. Educational Data Mining (EDM) focuses on extracting new knowledge using data from educational software, online courseware, academic records, and databases, etc. By looking at the vast amount of education that is now available, it has become possible to predict student performance, behavior, affect, and other constructs that could be related or has an impact to both the students' and Teachers' educational experience (Romero et al., 2010). In the Philippines, the Department of Education (DepEd) has been giving the National Achievement Test (NAT) to students in the basic education level since 2006 in lieu to the National College Entrance Examination (NCEE), which started in 1973 for graduating high school students.

Under the K to 12 System, part of the DepEd Order No. 55, s. 2016 is the administration of an achievement examination for Grade 12 to determine if the students meet the learning standards in senior high school, and this assessment will remain in force and effect until SY 2023-2024. In Ogena et al. (2018), showed that the prior performance of primary and secondary schools in the Philippines, both in national and international examinations, could be considered dismal. The new curriculum with the recent educational reform is adopted, but to ensure an improvement in the students' performance there must be a utilization of technology-driven research techniques.

The main objective of study is to develop a predictive model of the NAT performance of Senior High School students. In order to come up to that objectives this study needs to extract predictive features of students' NAT performance, find the extent of the relationship between the academic performance of the students in the previous and current year to their NAT performance and lastly to apply the result to reaching this must recommend pedagogical interventions in relation to the predictive features for NAT performance.

LITERATURE REVIEW

The Data Mining and Machine Learning Framework

Data Mining (DM) is an area of Computer Science which focuses on discovering novel and potentially useful information from large amounts of data (Baker, 2010).

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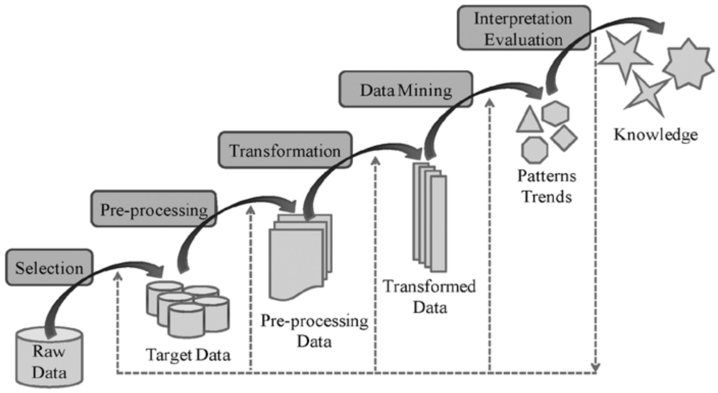


Figure 1. Data mining (DM) in knowledge discovery in databases (KDD)

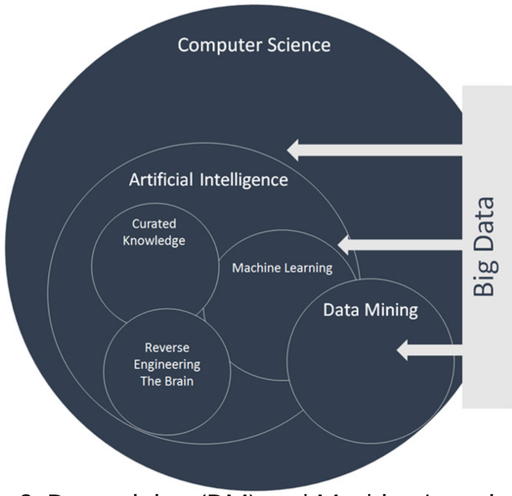


Figure 2. Data mining (DM) and Machine Learning (ML)
as related sub-fields in Computer Science

DM has been applied in various fields, including business, bioinformatics, and security. Over the years, there have been an increasing interest in leveraging DM techniques in educational research. Thus, the term Educational Data Mining (EDM) has been defined as the area of scientific inquiry focused in the development of methods to make discoveries with data coming from educational settings towards a better understanding of the students, developing pedagogical practices, and creating models for computer-based learning environments or educational software. For example, data mining can be used to study student behavior in using an educational software by considering data at the keystroke level, solution level, session level, etc. It could also be used to develop predictive models of student performance and identify features which could help design pedagogical strategies as intervention.

DM is part of the process of knowledge extraction called Knowledge Discovery in Databases (KDD) also called Knowledge Discovery in Databases (KDD), which was formally adopted in 1989 and refers to a process that involves the identification and recognition of patterns in a database, in an automatic way, i.e., obtaining relevant, unknown information, that may be useful in a decision making process, without a previous formulation of hypothesis (Figueiredo et al., 2016). Figure 1 shows the essential parts of KDD which involves data selection, pre-processing, transformation, data mining, and interpretation.

In relation to DM, Machine Learning (ML) is also a sub-field of Computer Science that focuses on designing algorithms that can learn from the data. ML is one of the many techniques used in DM to make predictions or classifications (Alpaydin, 2009). Figure 2 shows the relationship between DM and ML as sub-fields of Computer Science.

Machine Learning mainly divided into three categories: supervised, unsupervised, and semi-supervised (reinforcement). Supervised Learning, which will be used in this study, is the first type of machine learning, in which labeled data used to train the algorithms. In supervised learning, algorithms are trained using marked data, where the input and the output are known. We input the data in the learning algorithm as a set of inputs and the algorithm learns by comparing its actual production with correct outputs to find errors. It then modifies the model accordingly. The raw data is divided into two parts. The first part is for training the algorithm, and the other region used for test the trained algorithm. Supervised learning uses the data patterns to predict the values of additional data for the labels. This method is commonly used in applications where historical data predict likely upcoming events.

Prediction of Students' Performance using DM and ML

Over the years, the Philippines' basic education has shown below par performance in comparison to other countries specifically in the ASEAN region and one of the reasons cited for this was the 10-year curriculum structure. As a solution, the government ruled for the basic education system to shift to the K-12 structure (Cruz, 2015). However, efforts for improvement seemed futile as the performance got worse based on the 2017 Global Innovation Index where the Philippines ranked poorly at the 113th place out of 127 countries (Lugtu, 2018). To alleviate this, the Department of Education (DepEd) has been conducting the National Achievement Test (NAT) (DepEd Memorandum 146 series, 2018) in order to assess the quality of education provided to the students. Students' performance is a significant part in educational institutions because one of the criteria of quality is based on the excellent record of academic achievement.

Data mining techniques and various machine learning algorithms have proven to be effective in creating predictive models of student performance. Decision Tree is one of a popular technique for prediction. Most researchers have used this technique because of its simplicity and comprehensibility to uncover small or large data structure and predict the value(Naika & Zwilling, 2014; Osmanbegovic & Suljic, 2012; Quadri & Kalyankar, 2010). Jishan et al.(2015) and Naika & Zwilling (2014) were able to get more than 90% accuracy in predicting performance using Decision Trees. Bunkar et al. (2012) has also shown that this method is effective for the prediction of performance improvement of graduate students using a larger data set.

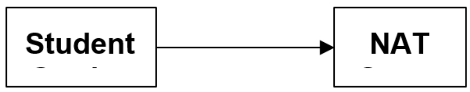
Another option for researchers to make a prediction is Naive Bayes algorithm. Devasia et al. (2016) proposed a web based application which makes use of the Naive Bayesian mining technique for the extraction of useful information. The experiment is conducted on 700 students' with 19 attributes in Amrita Vishwa Vidyapeetham, Mysuru. Result proves that Naive Bayesian algorithm provides more accuracy over other methods like Regression, Decision Tree, Neural networks etc., for comparison and prediction. The same result was shown in another research (Saa, 2016) where three different data mining classification algorithms (Naïve Bayes, Neural Network, and Decision Tree) were used on the dataset. The prediction performance of three classifiers are measured and compared and Naïve Bayes classifier outperforms other two classifiers by achieving overall prediction accuracy of 86%.

Moreover, the attribute that has been frequently used is cumulative grade point average (CGPA). Several researches have used CGPA as the main attribute to predict student performance (Abu Tair & El-Halees, 2012; Angeline, 2013; Osmanbegovic & Suljic, 2012; Quadri & Kalyankar, 2010). The main idea of why most of the researchers are using CGPA is because it has a tangible value for future educational and career mobility (Shahiri & Husain, 2015). It can also be considered as an indication of realized academic potential (Bin Mat et al., 2013) .

For school heads and teachers, analyzing NAT results would be helpful not only to determine the quality of teaching and learning but also in finding specific factors that contribute to the students' performance. This study aims to leverage the use of educational data mining in order to find those factors and so teachers could design pedagogical strategies to help students and improve their academic experience.

Logistic Regression outperform the other five algorithms in the study entitled "Use Educational Data Mining to Predict Undergraduate Retention" (Lehr et al., 2016). Logistic Regression showed 80% of the precision in the study about Applying Educational Data Mining to Explore Students' Learning Patterns in the Flipped Learning Approach for Coding Education (Hung et al., 2020). Evaluating the performance of other algorithms; Logistic Regression, Naive Bayes, and SVM logistic regression showed a higher percentage in accuracy, precision, and F1 Score, the study identifies the Drop Out students using Educational Data Mining. (Tasnim et al., 2019)

Independent And Dependent Variables



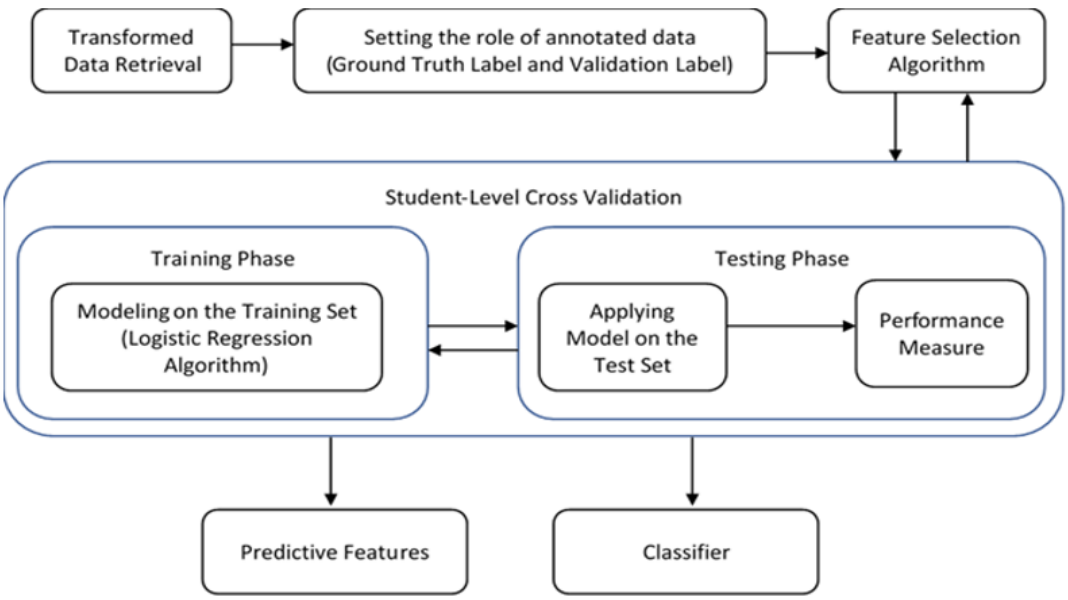


Figure 3. Logistic Regression with Feature Selection and Student-level Cross-Validation

In the diagram above, you can observe the independent and dependent variables. The dependent variable is the NAT Scores which the scores are categorized as Low Master and Very Low Mastery. The student grades retrieved from report cards with the following subjects are the dependent variables:

1. 21st Century Literature in the Philippines and the World
2. Pre-Calculus
3. Biology
4. Personal Development
5. Basic Calculus
6. Philosophy
7. Disciplines and Ideas in Social Science
8. Physical Science
9. English for Academic and Professional Purposes
10. Religion
11. Earth and Life Science
12. Reading and Writing Skills
13. Earth Science
14. Statistics
15. Filipino
16. Science
17. General Mathematics
18. Social Science
19. Information and Communication Technology
20. Understanding Culture Society and Politics
21. Mathematics
22. Creative Writing
23. Oral Communication
24. Physics

METHODOLOGY

This study implements the KDD (Knowledge Discovery in Database) methodology. Figure 3 shows the specific KDD (Knowledge Discovery in Database) methodology for this study using the Logistic Regression Algorithm and Feature Selection Technique. Basically the KDD methodology focuses on the Selection, Pre-processing, Transformation, Data Mining and Interpret Evaluation these are also the steps in this study.

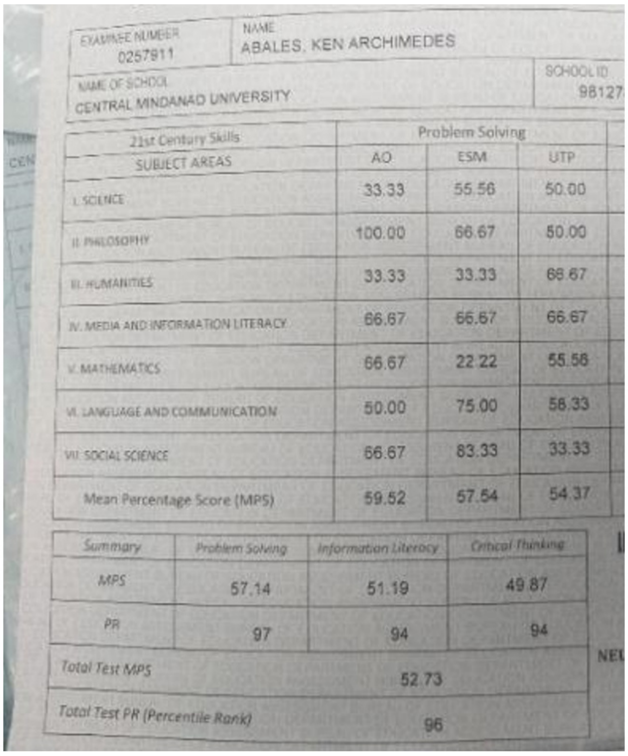
The coding of the Periodic Grades Dataset and the Union Operator in Rapidminer are both part of the selecting process. Pre-processing was the next step. Oversampling with Feature Selection Algorithm was used for the transformation. The Data Mining Process includes using logistic regression techniques throughout the training and testing phases. Finally, Designing the Strategic Intervention is under the category of interpret Evaluation.

Data

There are two data sources in this study: the Periodic grades dataset and the National Achievement Test dataset. All were collected from the college of Education of Central Mindanao University and in the form of hard copy.

The periodic grades data was about the student's subject performance grade when they were in grade 11 (The school Year 2017-2018) as well as their periodic grades in grade 12 (The school Year 2018-2019), before taking the National Achievement Test was collected from a total of 723 Senior High School students of Central Mindanao University.

The periodic grades of students are from the Four strands: 323 from STEM (Science Technology Engineering Mathematics), 159 from HUMSS (Humanities and Social Sciences), 94 from ABM (Accounting and Business Management), and 147 from TVL (Technical Vocational and Livelihood). The attributes are the students' subjects from their periodic grades in the 1st and 2nd Quarters in Grade 11 and 1st Quarter in Grade 12. There are a total of 23 subjects in the mentioned quarters of Grade Levels. There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NAME OF SCHOOL CENTRAL MINDANAO UNIVERSITY
SCHOOL ID 98127

21st Century Skills SUBJECT AREAS	Problem Solving AO	ESM	UTP
I. SCIENCE	33.33	55.56	50.00
II. PHILOSOPHY	100.00	66.67	50.00
III. HUMANITIES	33.33	33.33	66.67
IV. MEDIA AND INFORMATION LITERACY	66.67	66.67	66.67
V. MATHEMATICS	66.67	22.22	55.56
VI. LANGUAGE AND COMMUNICATION	50.00	75.00	58.33
VII. SOCIAL SCIENCE	66.67	83.33	33.33
Mean Percentage Score (MPS)	59.52	57.54	54.37

Summary	Problem Solving	Information Literacy	Critical Thinking
MPS	57.14	51.19	49.87
PR	97	94	94
Total Test MPS	52.73		
Total Test PR (Percentile Rank)	96		

Figure 4. National Achievement Test Certificate Rating

are different, related, and the same subjects in different quarters. After collecting the dataset from periodic grades, the National Achievement Test dataset from the College of Education scores was sorted and digitized by the research assistants.

Figure 4 shows the National Achievement Test Certificate. The exam coverage is composed of 7 categories; Science Philosophy, Humanities, Media and Information Literacy, Mathematics, Language and Communication, and Social Science. These categories' scores are displayed using the three 21st Century Skills; Problem Solving ability, Information Literacy Ability, and Critical Thinking Ability.

It is presented in the lower-left side of the certificate, the table for the score's summary. Which consist of the Mean Percentage Score (MPS) and the Percentile Rank per category – Problem Solving, Information Literacy, and Critical Thinking. Figure 4 summarizes all scores, the Total Test Mean Percentage Score, and the Total Test Percentile Rank of the three categories below the summary of all scores.

Selection

The subjects' names are too long; it is recommendable to code these subjects per quarter and Grade level. To follow the proper computer file naming convention. The format is:

subject-name-acronym-grade-level-quarter name

For example, Oral Communication has an acronym of OC, followed by the year-level acronym: G11 for grade 11, next is the Quarter's acronym, Q1 for quarter 1. The coded subject looks like this: OC-G11-Q1. Shown in Table 1, the subject code for the Periodic Grades Dataset.

In preparing for the National Achievement Test dataset, the first thing that we did is convert the hard copy to digital. The Mean Percentage Score was then classified, and according to Albano (2019), the NAT score follows the following criteria, shown in Table 2.

The criteria are dependent on the Mean Percentage Score of the National Achievement Test. Table 2, the range 0 – 35, is classified as Very Low Mastery, 36 – 65 as Low Mastery, 66 – 85 is classified as Average Mastery, and 86 – 100 as Moving Towards Mastery. The criteria are renamed based on its acronym: VLM for Very Low Mastery, LM for Low Mastery, AM for Average Mastery, and MTM for Moving towards Mastery.

The Periodic grades dataset and the National Achievement Test dataset were combined and then was separated per strand. There are a total of 4 strands: Humss, Stem, ABM, and TVL. The four files were combined using a union operator to avoid redundancy to the attributes and data while combining the datasets, shown in Figure 5. The union operator creates a superset from multiple example sets. If there is a common attribute in both exampleset, the union operator only creates one single attribute that will hold the data for both data sets.

Table 1. Subject code in Periodic Grades Dataset

1. 2CLPW	21st Century Literature in the Philippines and the World	13. PC	Pre-Calculus
2. B	Biology	14. PD	Personal Development
3. BC	Basic Calculus	15. Ph	Philosophy
4. DISS	Disciplines and Ideas in Social Science	16. PSc	Physical Science
5. EAPP	English for Academic and Professional Purposes	17. R	Religion
6. ELS	Earth and Life Science	18. RWS	Reading and Writing Skills
7. ES	Earth Science	19. S	Statistics
8. F	Filipino	20. Sc	Science
9. GM	General Mathematics	21. SS	Social Science
10. ICT	Information and Communication Technology	22. UCSP	Understanding Culture Society and Politics
11. M	Mathematics	23. CW	Creative Writing
12. OC	Oral Communication	24. P	Physics

Table 2. 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

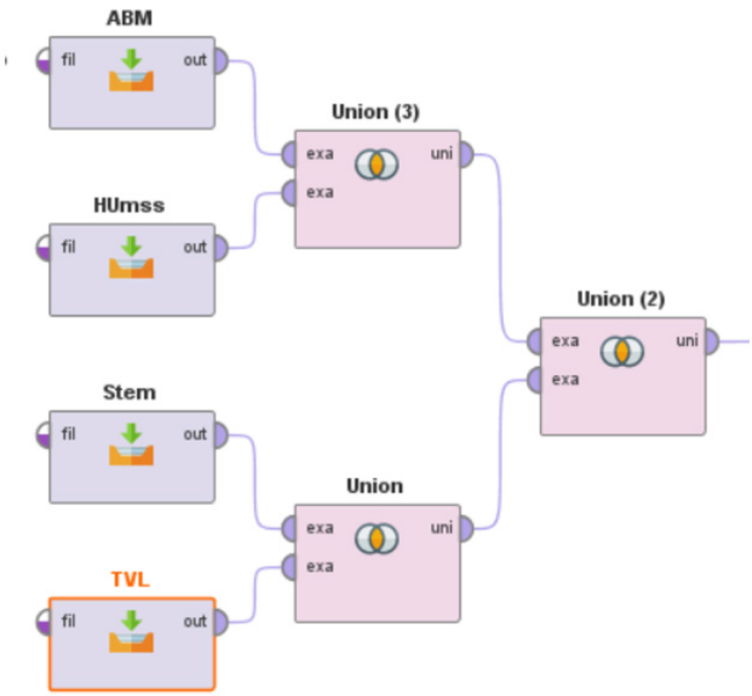

Figure 5. Union Operator in Rapidminer

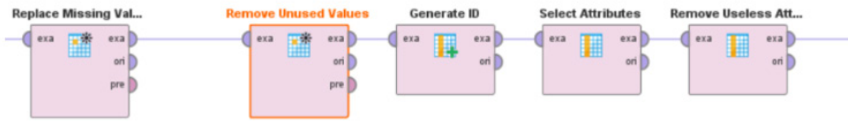

Figure 6. Preprocessing

Pre-processing

There are still inconsistent values in the dataset, like students without grades in some quarters, students that have not taken the National Achievement Test, and some other useless data. The Data Cleaning technique was done on this stage to replace the missing value, remove unused values, and remove useless attributes. Data Cleaning is part of the Preprocessing algorithm.

The preprocessing stage in rapidminer is in Figure 6.To uniquely identify the students; there is a need to generate the ID of all the students; the ID is necessary for the transformation phase. The select attributes operator is used to select only the attributes needed.

Transformation

The National Achievement Test Criteria is the output variable or the dependent variable assigned using the set role operator in this stage. The set role operator is used to set the dependent variable in rapidminer; the role should be the unique role label necessary in the Logistic regression algorithm.

The unique student ID is used as the batch label to ensure that a student's record will not be in the training set and the test set during the same iteration. An oversampling methodology was then applied because, upon the pre-assessment, there is an uneven/unbalanced amount of data. We found out that there are only two available NAT criteria in all the strand, VLM and LM. The LM (Low Mastery) has the most significant ratio, while the VLM has only 3%; this means most of the students got Low Mastery in the National Achievement Test.

An oversampling technique is necessary in order to balance data. The distribution of the oversampling techniques is 50% VLM and 50% LM.

A feature selection algorithm is optimized to iteratively develop a parsimonious model as the data will be going through training and testing.

Feature selection has improved the comprehensibility of extracted knowledge; it is the process of identifying and removing as much irrelevant information as possible (Hall,1999). The operator used selects the most relevant attributes of the given exampleset; the performance measurement is inside the operator to indicate how well the feature subset performs.

Logistic Regression Algorithm

The cross-validation was connected after the feature selection technique to train and test the dataset; to apply the model to the dataset and, at the same time, estimates how accurately a model will perform in practice. This operator has two subprocesses: the training and the testing subprocess. In the training subprocess, the logistic regression learns good values for all the weights, and the bias from labeled examples iteratively called training. There is a need to test the Logistic regression model to check the accuracy and validate the model prediction; then place the

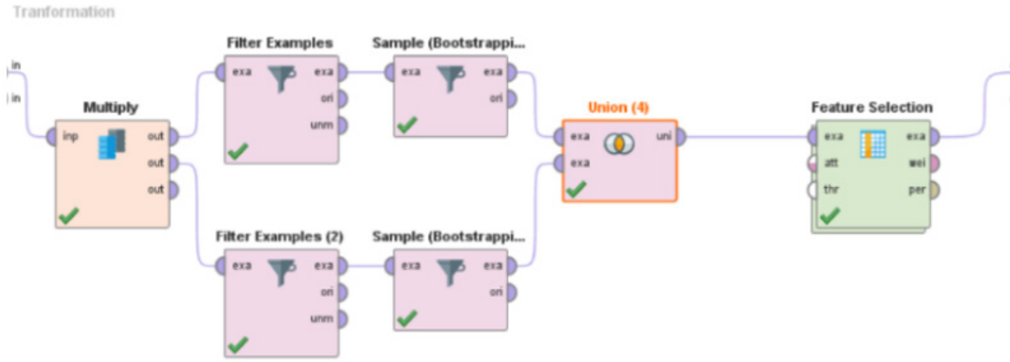

Figure 7.Oversampling with Feature Selection Algorithm

Figure 8. Logistic Regression Algorithm in Cross-Validation

applied model operator in the testing subprocess before the classification performance. Figure 8 shows the logistic regression in the training subprocess and performance classification in the testing subprocess.

There must be a partitioned subprocess to K subset then for testing the other subset must be retrained in cross-validation. Then the remaining K-1 will be applied to the training subprocess. This cross-validation will be iterated in K times, the usage of the partitioned K subsets will only be once.

Designing the Strategic Intervention

In order to design the strategic intervention it would be better to find out the pedagogical approach first thus, before finding out the pedagogical approach the interpretation of the data from the model must be considered. The process in interpreting in order to come up with the strategic intervention also known as the pedagogical approach will be expounded.

1. Identifying the Predictive Features - This part identifies the predictive features through the feature selection process. There are only 14 features being selected by feature selection, thus 2 subjects are repeated therefore there are only 12 subjects with significance to the National Achievement test based on the academic performance of students.These subjects are Earth and Life Science, Physical Science, Personal Development, Understanding Culture Society and Politics, 21st Century Literature in the Philippines and the World, Philosophy in quarters 1 and 2, Filipino, English for Academic and Professional Purposes, English for Academic and Professional Purposes, Filipino in Grade 11 quarters 3 and 4, Media and Information Literacy and lastly Arts.

2. Interpreting coefficients - in order to determine relationship between the National Achievement Test and the Periodic grades this part is about interpreting the coefficients that is given by the model. Since the coefficients may interpret the likelihood of the student to pass or fail in the National Achievement test based from the student performance, we have used these negative and positive coefficient values to interpret the data.

a. Negative Coefficient - A negative coefficient suggests that as the independent variable increases, the dependent variable tends to decrease.

b. Positive Coefficient - A positive coefficient indicates that as the value of the independent variable increases, the mean of the dependent variable also tends to increase.

3. Finding out the strategic intervention - this is about researching and looking for references to be adopted in finding out what kind of pedagogical approach is recommended based from the result of the model.

RESULTS & DISCUSSIONS

The Predictive Model

The algorithm that was used for this study is the logistic regression model. Supposedly there will be 4 values being extracted from the National Achievement Test scores thus, upon observing the datasets and values of NAT student grades there are only 2 values: Very Low Mastery and Low Mastery

The developed Logistic regression predictive model of the NAT performance of Senior High School students shown in Tables 3, 4,5 and 6.

Out of 30 attributes, there were only 14 that were selected by feature selection technique. 9 out of 14 are the subjects in Grade 11, and the remaining five subjects are from

Table 3. Predictive Model of the National Achievement Test Performance of Senior High School Students of Physical Science (Physical Scie), Personal Development(PerDev), Understanding Culture Society and Politics(UCSP).

Variables	Physical Scie	PerDev	UCSP
Grade	11	11	11
Quarter	4	2	1
Coefficient	-17.11	-4.1	-4.89
Std. Coefficient	-9.11	-15.61	-8.07
Standard Error	7.03	1.2	1.91
Wald	-2.43	-3.42	-2.56
p-value	0.01	0	0.01

Table 4. Predictive Model of the National Achievement Test Performance of Senior High School Students in 21st Century Literature in the Philippines and the World(CLPW), Philosophy, English in Academic and Professional Purposes(EAPP).

Variables	CLPW	Philosophy	EAPP
Grade	12	12	11
Quarter	1	2	2
Coefficient	-1.93	-1.36	-30.97
Std. Coefficient	-6.71	-13.67	-10.6
Standard Error	0.9	0.51	11.79
Wald	-2.14	-2.63	-2.63
p-value	0.03	0.01	0.01

Table 5. Predictive Model of the National Achievement Test Performance of Senior High School Students in Filipino, Media and Information Literacy(MIL), Earth and Life Sciences(ELS)

Variables	Filipino	MIL	ELS
Grade	11	12	11
Quarter	3	1	2
Coefficient	-0.65	-1.04	2.75
Std. Coefficient	-4.32	-6.06	3.76
Standard Error	0.75	0.58	3.3
Wald	-0.87	-1.78	0.84
p-value	0.38	0.08	0.4

Table 6. Predictive Model of the National Achievement Test Performance of Senior High School Students in Filipino for grade 11 in 2nd and 4th quarter, EAPP(English in Academic and Professional Purposes) and then Arts

Variables	Filipino	EAPP	Filipino
Grade	11	11	11
Quarter	2	1	4
Coefficient	0.46	18.32	0.15
Std. Coefficient	3.01	7.88	1.24
Standard Error	0.39	9.45	0.69
Wald	1.18	1.94	0.22
p-value	0.24	0.05	0.82

Grade 12. The model displayed five attributes; Coefficient, Standard Coefficient, Standard Error, Wald, and the P-Value. Each of the attributes is significant in the analysis and plays a vital role in prediction.

The academic performance of the students and NAT performance

National Achievement Test and Periodic Grades Relationship

The coefficient value signifies how much the dependent variable changes given a one-unit shift in the independent variable while holding other variables in the model constant. Table 3 shows the Coefficient of independent variables extracted by the feature selection algorithm.

The more the students got high grades in the subjects listed in Table 6, the less likely these students will get Low Mastery Grade. These subjects are Understanding Culture Society and Politics in Quarter 1, Personal Development and English for Academic and Professional Purposes in Quarter 2, Filipino in Quarter 3, and Physical Science in Quarter 4 from Grade 11. Then another two subjects from Grade 12 both in Quarter 1: Media and Information Literacy and 21st Century Literature in the Philippines and the World. Then one subject from Quarter 2 of Grade 12, Philosophy.

The positive Coefficient implies that the more the students get higher grades on these subjects listed in Table 7, the more likely they will get Low Mastery. It also implies that the more the student gets high grades, the less likely they will get a Very Low Mastery criterion in the National Achievement Test. The subjects are English for Academic and Professional Purposes in Grade 11 Quarter 1. Earth and Life Science and Filipino in Grade 11 Quarter 2. Arts in Grade 12 Quarter 2 and Filipino in Grade 11 Quarter 4.

English for Academic Purposes from Grade 11 in Quarter 1 has a positive coefficient of 18.32. It implies that the more the student gets higher grades in this subject in the specific Quarter, the more likely the student will get Low Mastery. Then the negative Coefficient of -30.97 in Quarter 2 of the same subject implies that the more the student gets higher grade in this subject, the less likely these students will get Low Mastery Grade or the more likely these students could get a Very Low Mastery National Achievement Test Result Rating. English for Academic Purposes in Quarter 1 of Grade 11 showed the most substantial effect in the National Achievement Test performance rating.

Figure 9 shows the Result per Subject Category Coverage. 37.5% of all the subject implies, the higher the student's grade in Social Science and Personal Development, the less likely the student will get Low Mastery. 25% implies the higher the grade in Language and Communication, the less likely the student will get Low Mastery. 12.5% implies the higher the grade in Science, the less likely the student will get Low Mastery.12.5% implies that the higher the grade in Media and Information Literacy, the less likely the student will get Low mastery. 12.5% implies the higher the grade in Philosophy, the less likely the student will get Low mastery.

Figure 10 shows the result per category coverages.

Table 6. Negative Coefficient:

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

Table 7. Positive Coefficient:

Subject	Grade Level	Quarter	Positive Coefficient
English for Academic and Professional Purposes	Grade 11	Quarter 1	18.32
Philosophy	Grade 12	Quarter 1	1.13
Earth and Life Science	Grade 11	Quarter 2	2.75
Filipino	Grade 11	Quarter 2	0.46
Arts	Grade 12	Quarter 2	2.70
Filipino	Grade 11	Quarter 4	0.15

Figure 9. The higher the periodic grades in these Subject Categories, the less likely the student will get Low Mastery.

Figure 10. The higher the periodic grade in these Subject Categories, the more likely the student will get Low Mastery

50% of subjects belonging to the Language and Communication category coverage implies that the higher the periodic grade in this category, the more likely the student will get Low Mastery. Then, 17% from Philosophy, Science, and Humanities category implies, the higher the periodic grade in this category, the more likely the student will get Low Mastery.

The Relationship and Effect of the academic performance to National Achievement test

The Second highest absolute value coefficient is the Arts in the Second Quarter of Grade 12, shown in table 6. It means it has the second-highest effect on the Student's National Achievement Test performance among all the subjects. The Art's (Quarter 2, Grade 12) coefficient implies that the more the student gets the higher grade, the more likely they will get Low Mastery and other National Achievement Test Criteria except for Very Low Mastery. This attribute is accepted and statistically significant based on its P-value, as shown in Table 8.

There are two Filipino subjects from different Quarter and the same grade level; the positive Coefficient implies that the more the student got higher grades in quarters 2 and 4, the more likely they will get Low Mastery since Filipino is not on the list of Std. Coefficient's Highest Absolute Value table implies that this subject does not affect the National Achievement Test Student Performance. The P-Value is above .05, which means it is not statistically significant to the National Achievement Test.

Standardized regression coefficients are frequently used in quantitative social sciences and are very useful in many purposes: Selecting variables, determining the relative importance of explanatory variables, comparing the effect of changing different variables, and so forth (Bring,1994). Menard(2011) cited the works of Agresti (1996); one of the reasons for using standardized coefficients is that when variables are measured in different units of measurement, standardized coefficients are useful for comparing the relative strength of different predictors or independent variables within a multiple regression or logistic regression model. The higher the absolute value of the standardized Coefficient, the stronger the effect (Glen, 2016).

There is sufficient evidence to conclude a significant linear relationship between the National Achievement Test and y because the correlation coefficient is significantly different from zero.

The results of the logistic regression model show that Filipino students in Grade 11 in Quarters 2, 3, and 4 had the greatest impact on the National Achievement Test; as a result, a path analysis was conducted solely for subjects with substantial impact. The subject Filipino in grade 11 in quarters 2, 3, and 4 has a significant impact on the National Achievement Test, according to the Model. As seen in the path analysis in Figure 11, Filipino in grade 11 in quarter 4 and quarter 2 has a positive and significant impact on the National Achievement Test. On the other hand Filipino in Grade 11 of Quarter 3 has a negative and significant impact on the National Achievement Test.

Filipino in Grade 11 of Quarter 2 and Quarter 4 has a direct effect in the National Achievement Test Score as seen in table 8. Filipino in Grade 11 of Quarter 3 indirect effect on the National Achievement Test as seen in Table 9..

Validation

The Confusion Matrix shows VLM's predicted

Table 8 Subject arrangement based on the P-Value

Variables	Grade	Quarter	Wald	P-Value
Physical Science	11	4	-2.43	0.01
Personal Development	11	2	-3.42	0.00
Understanding Culture Society and Politics	11	1	-2.56	0.01
21st Century Literature in the Philippines and the World	12	1	2.14	0.03
Philosophy	12	1	2.56	0.01
Philosophy	12	2	-2.63	0.01
English for Academic and Professional Purposes	11	2	-2.63	0.01
Arts	12	2	4.73	0.00

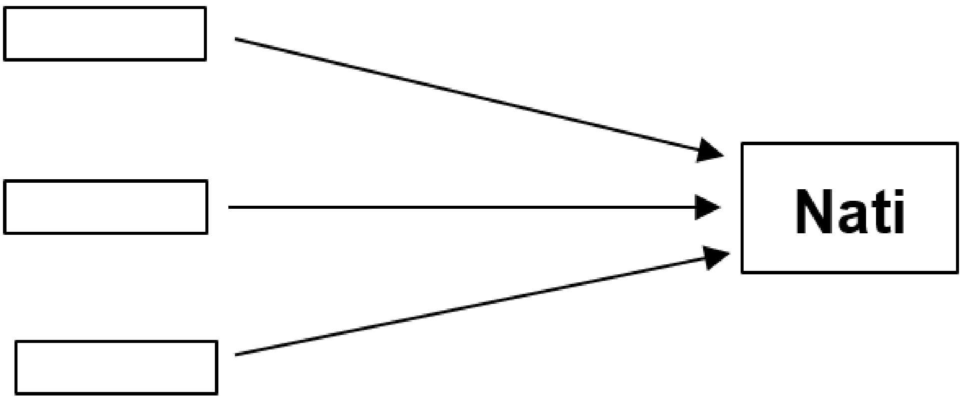

Figure 11. Path Analysis based on correlation coefficient with significant impact

Direct Effect	Predictive Value
Filipino G11, Q2	.46
Filipino G11, Q4	.15
Indirect Effect	**Predictive Value**
Filipino G11, Q3	-.65

Table 9. Subjects with Direct and Indirect Effect based from the Predictive Value

values (Very Low Mastery) and LM(Low Mastery). 42.85% of the population got a National Achievement Test Rating of Very Low Mastery with a yield sensitivity of 96.33% with a fair kappa rating of .852.

Model Fitting

R^2 is a metric that measures how well a model fits the data in regression (Leibler, 1995). This number can range between 0 and 1, with higher values suggesting greater model fit. In this analysis the R^2 resulted in 1. It would suggest that the model fits the data

CONCLUSION

Upon developing the predictive features, we found out that the feature selection technique selected only 14 subjects. It shows that the subjects in Grade 11 are more significant in the National Achievement Test Rating. As shown in the tables, the subjects in the 1st Semester of Grade 11 have the highest significant attributes.

This analysis shows that the higher the grade in Social Science and Personal Development, the less likely the student will get Low Mastery. The higher the periodic grade in Language and Communication specifically English for Academic and Professional Purposes, the more likely the student will get Low Mastery.

We found out that the Philosophy in the 2nd Quarter of grade 12 shows the more significant effect in the National Achievement Test Score among all the subjects. This Quarter's subject also means that the more the students got a high periodic grade, the more likely these students will get Very Low Mastery Grade.

The student is putting so much attention and effort into the subject before the National Achievement Test could also be a factor. Arts in grade 12 of Quarter two, on the other hand, shows the 2nd subject with a more significant effect on the National Achievement Test. The more the students get higher grades in the mentioned subject and Quarter, the less likely they will get a Very Low Mastery criterion in National Achievement Test. It may also imply that those students enjoyed the Arts, the student will be more likely to get a higher criterion in the National Achievement Test.

There are two significant subjects in the 2016 – 2017 National Achievement Test Ratings: Philosophy and

Table 10. 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%

Arts, both from different categories. These are the only selected subjects of the feature selection from Grade 12 Quarter 2, a semester, and a quarter before the National Achievement Test Exam. The two subjects' results displayed that those students with a higher grade in philosophy are more likely to get a Very Low Mastery criterion.

On the other hand, those students who got higher grades in Arts are more likely to have higher results on the National Achievement Test. There are different factors of the student getting higher grades in their subject, looking at the result, the factor may affect the student performance in the National Achievement Test.

The pedagogical intervention depends upon a specific subject, and the pedagogical approach that is more recommended for Philosophy is reflective and constructivist. In constructivist theory, the learners have to construct their knowledge individually and collectively (Kumari,2014). The study of Navaneedhan (2011) resulted in a significant relationship between reflective teaching methodology and professional training. According to his study, the reason is that when an individual practices reflective teaching methodology by asking self-inquiry questions based on a set of learning objectives, it results in the refining of the individual's ability leading to professional training.

The effect of these subjects varies in the National Achievement test Result. Based on the result, if the student puts more effort and attention into a specific subject before the National Achievement Test, they will be more likely to get a lower National Achievement Test score.

RECOMMENDATIONS

It may be appropriate to try the study in other schools in Bukidnon or the whole Senior High School in Bukidnon to identify other factors why students usually get lower results on the National Achievement Test. It is also recommended to apply the pedagogical approach to these students' set and find out how effective the pedagogical approach. Finding the factors why Philosophy is statistically significant to the lower score in the National Achievement Test and finding the factors why Arts are statistically significant to a higher National Achievement Test may lead to another research study. Subjects that were not included to the selection might need further study. It may not mean that is has no impact or other factors might affect as to why these subjects were not selected.

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