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Algorithmic Analytics for Outcomes-based Tertiary Education Performance Assessment

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ABSTRACT

Global educational institutions are continuously working to enhance the needed curricula to answer the demands of state and business enterprise. They are now working with Outcomes-based Education (OBE), which denies the traditional way of education to students. Instead, it makes students show that they are capable of doing the required learning outcomes. The quest for learning the correct assessment for education while under the era of OBE is still an on-going call. With the help of Educational Data Mining, a real-world dataset of 549 were trained from the student record. The study intends to identify the probability of the student to pass practical evaluation following OBE methodology, using selected WEKA-based classifiers, namely Naive Bayes, C4.5, and Random Forest. The said classifiers revealed promising accuracy of 78.10% for Naïve Bayes, 93.07% for C4.5, and 95.99% for Random Forest. Hence, the EDM's future is really for further study, which can be implemented in the fields of entertainment, industry, medicine, and many others because of massive raw databases.

Key words: C4.5, EDM, Naïve Bayesian, Outcomes-based education, Random Forest

1. INTRODUCTION

Outcomes-based Education is a student-focused, results-based way of dealing with learning [1]. It steers evaluation towards specific targets, namely what students ought to take care of and what merits understanding in a content-heavy educational program [2]. Educators and students center on the ultimate ideal outcomes of each learning procedure, which continuously evaluates the discovery of whether they are gaining any grounds or not [1].

An essential concern to be asked by an OBE program product to instruction and education is if they are capable of using what they have studied in a realistic environment, which attempts to explore higher-order thinking skills competencies and their meanings used in OBE [1].

With the intense focus on desired education outcomes in higher education [3], academic institutions all over the world have been under growing strain from governments to exhibit competence, furthermore, cost-effectiveness through more significant and precise reporting of program outcomes [4]. In nations, for example, Australia [2], [3], Canada [5], the United States [3], [5], the UK [3], South Africa [1], and New Zealand [2], [3], [5], OBE is, at present, implemented and supported globally to elevate educational renovation [5]. The emphasis considering learning outcomes has given a lift to interests about the extreme weight on the conducive and economic worth of education that is measured through competence and effectiveness in the contemporary educational context [3].

Learning assessment is, therefore, the essential methodology by which the desired learning outcomes described by a unit of learning, indeed credited as the discovering significance [6] and the authentic end-results or worth earned by a learner, that should mold from potential to actual [7]. It is promoted by research that the means of assessment should be for quality before deployment [1]. There are varied yet relevant kinds of evaluation in academic institutions, including assessment, end-results, attrition analysis, and retention. Also, there are some refined alternative models of evaluation, including curriculum-based [8], outcomes-based [9], [10], and performance-based assessment [11], [6].

Concerning education today, the utilization of Data Mining is fit [12] for data learning, decisions-support, and instruction [13]. The application of DM in the field of education is developing. It serves as the beginning of educational data mining (EDM) study [14] because instead of seeking natural resources, it targets educational knowledge [13], [15] to adequately know the student learning setting [16]. EDM does various data mining methods such as Neural Networks (NN) [15], Decision Trees (DT), Naïve Bayes (NB) [17], K- Nearest Neighbor (KNN), Random Forest (RF), Support Vector Machine (SVM) [17], and many others [15], [18], [19].

The study concerns the prediction analysis of student's performance assessment under the rig of Outcomes-based Education (OBE). In determining the possible outcomes systematically, the study used Naïve Bayes [17], C4.5, and Random Forest [16]. Through this, it will generate an imminent approach as to how likely a student will right-fit to OBE through data interpretation and student performance, given the implementation of OBE methodology.

Figure 1 shows several significant measures included in OBE, including determining assessment measures.

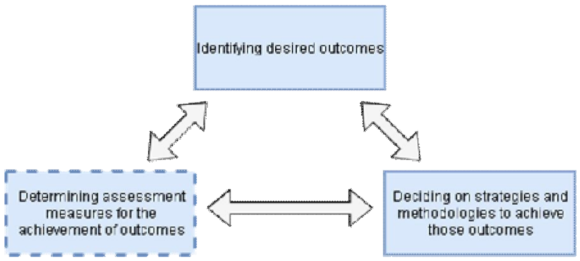


Figure 1: OBE being an Approach [17]

2. LITERATURE REVIEW

2.1 Review Stage

In working this research out, a literature review holds out to interpret its current position. This is to support the idea gathered in redefining the contextual basis for OBE assessment data analysis.

Educational Data Mining (EDM) is still new in terms of Data Mining procedures [16], which has been introduced as a future research field correlated to various buttoned-down operations of studies, including AH, DM, e-learning, ITSs, WM, and many others [20]. EDM can also work in areas such as accounts, politics, sports, transportation [16], business, genetics, medicine [20], and a lot more [16], [20] because it merely reflects exact ways as the overall DM process such as preprocessing, DM, and postprocessing [20]. As stated above, EDM uses various data mining techniques. Hence, it helps discover knowledge from data coming from the educational environment [21].

2.2 Classifiers

A. Naïve Bayes

As described by the author in [18], that, since, Naïve Bayes (NB) is the most famous analysis algorithm, due to its plainness [22] and efficiency that matches the concept of probabilities, it is applied in labeling data for analysis purposes [18]. There was a classification as positive or negative based on their ratings using movie reviews. Following the experimental evaluations, the system scored an accuracy of 83%. Another application of NB used a training set consists of 1500 questions for every 20 classes of the newsgroup. NB achieved an accuracy of 1 for class 1 and 0.58 for class 2. The same training set used, and SVM generated a different accuracy of 0.95 for both classes 1 and 2 [17]. The study commands a different method in getting the probability of the instance given with a precise dataset [22]. As it said on [23], Naïve Bayes is frequently applied as a baseline classifier, which measures other classifiers that consistently gives rational classification performance [23].

As shown in equation (1), a dependent probability is a probability that case "c" will happen, given the proof "x", which written usually as P(c | x). The Naïve Bayes Theorem permits to define the odds when all left is the probability of the contrary conclusion and the two elements only [24]:

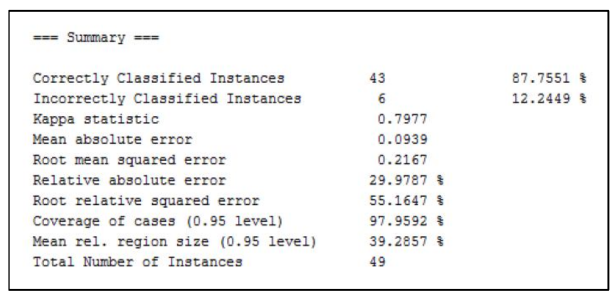
$$P(c|x) = \frac{P(x|c)P(c)}{P(x)} \tag{1}$$

When attempting to determine the probability of things, this restatement (1) can stay pretty significant based on occurring instances [24].

B. C4.5

Algorithms [16], [25], including C4.5 or J48 in WEKA, were used in classifying similarly [26], predicting attainment [25], and achieving returns from hypothesis experimentation [16]. It showed that the type of schools does not affect student performance, but it is the parent's job who plays a significant part in predicting grades [16]. A study for university students revealed that the C4.5 decision tree algorithm is used in the prediction, analysis, and prevention of their academic failure, specifically, examination failure [20].

Retrieved results from the implementation of the C4.5 algorithm in the university containing students' records [26], as shown in Figure 2.



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=== Summary ===

Correctly Classified Instances          43               87.7551 %
Incorrectly Classified Instances         6               12.2449 %
Kappa statistic                          0.7977
Mean absolute error                      0.0939
Root mean squared error                  0.2167
Relative absolute error                 29.9787 %
Root relative squared error             55.1647 %
Coverage of cases (0.95 level)          97.9592 %
Mean rel. region size (0.95 level)      39.2857 %
Total Number of Instances               49
```

Figure 2: Generated Results after the Implementation of C4.5 Decision Tree [26]

Compared to other algorithms [27] like the k-means clustering technique [26], C4.5 is a single custom of foretelling end-results that promptly creates decision trees with high precision, yet it is more when it comes to cost-effectiveness [27] and efficiency [26].

Comparison of various classification techniques. Both C4.5 and Naïve Bayes went on top [17], as shown in Table 1.

Table 1. Comparative Interpretation of Classification Techniques [17]

Classifier	Processing Time (sec)	Correctly classified instances (%)	Incorrectly classified instances (%)	Kappa statistic	Mean absolute error	Root mean square error
J48	0.02	90	10	0.7692	0.146	0.3018
Naïve Bayes	0.01	85	15	0.625	0.1896	0.3497
OneR	0	70	30	0	0.3	0.5477
ZeroR	0	70	30	0	0.4238	0.4594
Ibk	0	68.3333	31.6667	0.2339	0.3312	0.5566

C. Random Forest

One of the fittest algorithms is Decision Trees, in terms of data classification, giving high accuracy for various problems in a comparatively brief time [28]. Both DTs and Naïve Bayes are used in EDM [16]. DT termed as decision support media that are typically done in decision study problems to support the classification of the most right-fit approach for attaining a solid goal [28].

[18] also mentioned the importance of Random Forest and matched its review with other classifiers. [18] supports the claims of [29] that the Random Forest algorithm gives practical and discriminative analysis resulting in a point that it is considered a competent classifier. RF was used to predict ultimate student production and forecast, which students might not pass [13] or as termed by [20], "drop out". In terms of micro average, RF is also known for its optimal performance [18].

Just like Naïve Bayes and C4.5, Random Forest has been used to foretell the students' outcomes based on a suggested guide, as mentioned in [30].

Data set evaluation results using C4.5, Naïve Bayes, and Random Forest Algorithms [30], as shown in Table 2.

Table 2. Results after the Evaluation of Dataset used in [30]

Algorithms	**Total Instances**	**Correctly Classified**	**Incorrectly Classified**	**Kappa Statistic**	**Means Absolute Error**	**Root Mean Squared Error**	**Relative Square Error**	**Root Relative Squared Error**
J48	60	56(93.3333%)	4(6.6667%)	0.8821	0.081	0.2012	20.7986%	45.7577%
Naïve Bayes	60	52(86.6667%)	8(13.333%)	0.7688	0.116	0.2369	29.7928%	53.8798%
Random Forest tree	60	60(100%)	0(0%)	1	0.0804	0.1175	20.6576%	26.7167%

3. METHODOLOGY

3.1 Process

When it comes to giving importance to students' scores, this study is anchored to [31], [32] about the type of assessment system being used in outcomes-based [31]. This is also supported by [33], especially on higher education [34], which is preparatory for each individual to the real-working world [14], [33].

Once the current EDM progress improvement, it is conserved and developed. Then, it will undergo content-organization, content-analyzation, and content-discussion of the study based on end-results provided by a DM approach [13]. This study used the application of the Knowledge Discovery Process, which was also performed by [15], [16], [18], [30], [26], as shown in Figure 3.

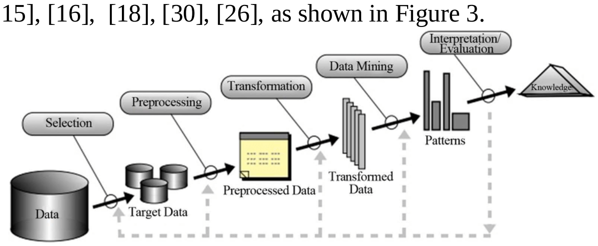

Figure 3: Knowledge Discovery Process [30]

Using the type of data-to-information transformation approach mentioned above [15], [30]. This gathered the records of first-year, Bachelor of Science in Information Systems and Information Technology students of Davao del Norte State College, for the academic years 2018-2019 and 2019-2020. The data gathered were used for prediction analysis, as shown in Figure 4, which is anchored to the conceptual framework solely dedicated to this study.

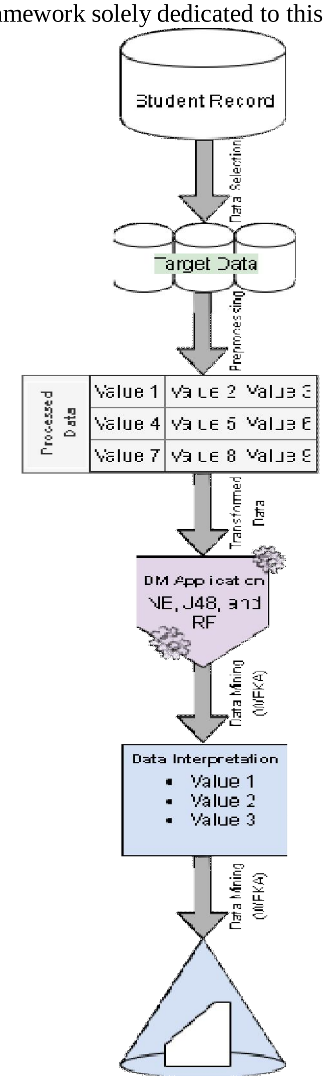

Figure 4: Conceptual Structure of the Study

3.2 Datasets

In this study, a sum of 549 students' records from the two sets of 1st-year class records of BSIS and BSIT, at DNSC, 1st semester, academic years from 2018-2020, were used as datasets which are shown in Table 3. The data obtained were cross-referenced from the Institute of Information Technology records held by the Program Chairpersons and database of the Integrated Academic Information Management System (IAIMS) that will be trained to achieve optimal accuracy for data mining.

Table 3. Data specifics

AY	**BSIT**					**BSIS**		**Total**
	Set A	**Set B**	**Set C**	**Set D**	**Set E**	**Set A**	**Set B**	
2018-2019	40	40	40	39	38	41	40	278
2019-2020	40	39	38	38	35	41	40	271

3.3 Data Preprocessing

To add more precision, data preprocessing was performed by challenging the variables, as shown in Table 4 and their data [14][21][27]. This is to make the mining method less confused when it comes to the identification, interpretation, and analysis of data. As per the academic year: 2018-2019 enrollment report, there is a total of 278 students, and the academic year: 2019-2020 enrollment has 271 after official and unofficial dropouts.

Table 4. Assessment-related variables with description and possible values

Variable	Description	Possible Value	Class Type
Age	Student's age	a=17-19 yrs. old; b=20-21 yrs. old; & c=22 yrs. old and up	Multi-class
Gender	Student's gender	Male; Female	Binary
Type of Learner	The type of learner the student is	Auditory; Kinesthetic; Visual	Multi-class
K-12 Grad	If the student went in the old or new curriculum	Yes; No	Binary
SHS Strand (ICT)	If graduate of SHS, does the student have the strand of ICT	Yes; No	Binary
Resource Availability	DNSC's computer laboratory to students ratio %	%(Headcount/Total # of available computer units) a=70%-80%; b=80.99%-90%; c=90.99%-100%	Multi-class
Owned Personal Unit	If the student has his/her own PC	Yes; No	Binary
Class Attendance	Student's class attendance	%(No. of instance (Present)/Total # of meetings) a=70%-80%; b=80.99%-90%; c=90.99%-100%	Multi-class
Q, A, CP, & Pr=100%	Average of student's quizzes, assignment, class participation, and project=100%	a=70%-80%; b=80.99%-90%; c=90.99%-100%	Multi-class
Paper & Pen Evaluation-0.4%=100%	Student's evaluation range from the traditional paper & pen examination=100%	a=70%-80%; b=80.99%-90%; c=90.99%-100%	Multi-class
Practicum Evaluation-0.6%=100%	Student's evaluation range from the laboratory examination under OBE=100%	low=70%-80%; ave=80.99%-90%; high=90.99%-100%	Multi-class

3.3 Data Mining

DM can give extensive yet specific prediction and decision-making, which is applicable in the field of academes, such as students' grades, GPA, drop rate, recommendation, and many others [12]. In achieving machine learning and DM, a modern tool applicable to education, WEKA toolkit has to be employed [16]. WEKA holds an extensive set of advanced Java-based ML and DM algorithms [14]. It includes instruments for and visualization. In making the gathered data compatible upon using the WEKA DM toolkit, it has to be prepared and changed to (.arff) file format [14][27].

4. RESULT AND DISCUSSION

With the application of C4.5, Naive Bayesian, and Random Forest algorithms through 5-fold and 10-fold Cross-Validation and Percentage Split of 70%:30% test options in WEKA, the training of datasets showed competitive results, which are somehow similar to the existing studies used, for example [30]. A sample of the dataset used for training is shown in Table 5.

Table 5. Sample from the entire dataset

Age	Gender	Type of Learner	K-12 Grad	SHS Strand (ICT)	Resource Availability %	Owned Personal Unit	Course Subject Retaker	Class Attendance %	Q, A, CP, & Pr=100 %	Paper & Pen Evaluation-0.4%=100%	Practicum Evaluation-0.6%=100%
a	male	visual	yes	yes	b	no	no	c	b	b	high
a	female	auditory	yes	no	b	no	no	c	b	a	high
a	female	kinesthetic	yes	yes	b	yes	no	c	c	b	high
a	male	visual	yes	yes	b	no	no	c	c	b	high
a	female	auditory	yes	no	b	no	no	c	b	b	high
b	male	visual	yes	no	b	no	no	c	b	a	low
…	…	…	…	…	…	…	…	…	…	…	…
…	…	…	…	…	…	…	…	…	…	…	…

As shown in Figure 5, WEKA pictures the allocation of values of the student records.

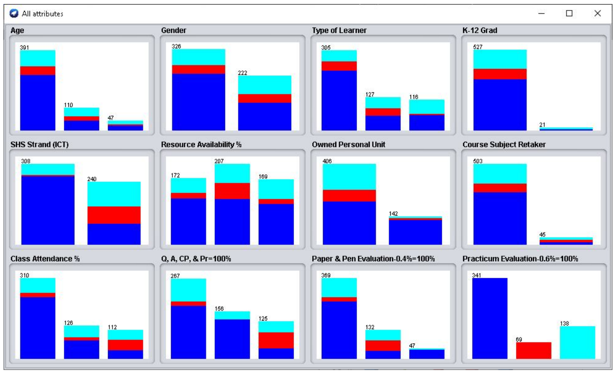

Figure 5: Students' Records Categorization Visualization

In predicting the student's performance, some tests were performed to assess the achievement and excellence of various classification algorithms [14]. Each algorithm has undergone each test option, as mentioned above, including Naïve Bayes that is shown in Table 6.

Table 6. Naïve Bayes' results specifics on applied test options

Summary	5-fold Cross-validation	10-fold Cross-validation	Percentage Split (70%:30%)
Correctly Classified Instances	426 (77.7372%)	428 (78.1022%)	115 (70.122%)
Incorrectly Classified Instances	122 (22.2628%)	120 (21.8978%)	49 (29.878%)
Kappa statistic	0.5845	0.5937	0.4582
Mean absolute error	0.1919	0.1916	0.2145
Root mean squared error	0.3207	0.3202	0.3499
Relative absolute error	53.8542%	53.7944%	59.7609%
Root relative squared error	76.0531%	75.9208%	82.0225%
Total Number of Instances	548		164
Detailed Accuracy By Class (Weighted Avg.)	**5-fold Cross-validation**	**10-fold Cross-validation**	**Percentage Split (70%:30%)**
TP Rate	0.777	0.781	0.701
FP Rate	0.16	0.159	0.223
Precision	0.782	0.787	0.705
Recall	0.777	0.781	0.701
F-Measure	0.779	0.784	0.703
MCC	0.616	0.617	0.472
ROC Area	0.89	0.887	0.845
PRC Area	0.841	0.836	0.810
Class	high/low/ave		

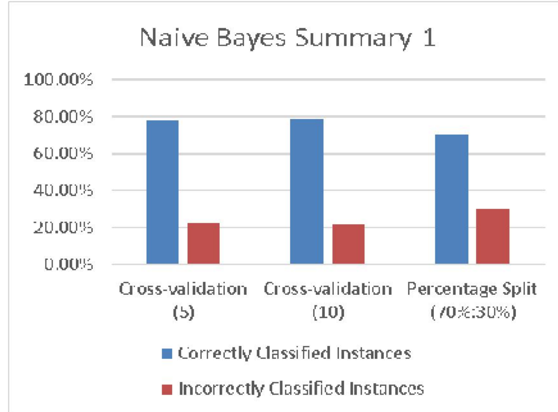

Figure 6: Naïve Bayes Test Options Results Visual Representation

Amongst the three-Test Options used in dataset training, the 10-fold Cross-validation that gave a promising result of 78.1% for Correctly Classified Instance, as shown in Figure 6.

A set of analyses were performed on the same Test Options employing C4.5 and RF algorithms, which presented assuring results. A tabular and graphical representation of results of both C4.5 and RF classifiers after 5 and 10-fold CV and PS of 70%:30% are shown in Figures 7 and 8 and Tables 7 and 8.

Table 7. C4.5's results specifics on applied test options

Summary	5-fold Cross-validation	10-fold Cross-validation	Percentage Split (70%:30%)
Correctly Classified Instances	504 (91.9708%)	510 (93.0657%)	137 (83.5366%)
Incorrectly Classified Instances	44 (8.0292%)	38 (6.9343%)	27 (16.4634%)
Kappa statistic	0.8466	0.8682	0.6921
Mean absolute error	0.0527	0.433	0.1168
Root mean squared error	0.1893	0.1681	0.2996
Relative absolute error	14.7866%	12.1625%	32.5388%
Root relative squared error	44.899%	39.8589%	70.2220%
Total Number of Instances	548		164
Detailed Accuracy By Class (Weighted Avg.)	**5-fold Cross-validation**	**10-fold Cross-validation**	**Percentage Split (70%:30%)**
TP Rate	0.92	0.931	0.835
FP Rate	0.07	0.061	0.138
Precision	0.918	0.930	0.831
Recall	0.920	0.931	0.835
F-Measure	0.918	0.930	0.830
MCC	0.864	0.881	0.712
ROC Area	0.986	0.991	0.914
PRC Area	0.975	0.985	0.857
Class	high/low/ave		

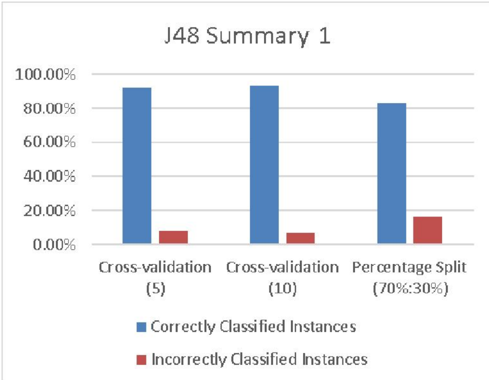

Figure 7: C4.5 Test Options Results Visual Representation

Table 8. RF's results specifics on applied test options

Summary	5-fold Cross-validation	10-fold Cross-validation	Percentage Split (70%:30%)
Correctly Classified Instances	523 (95.438%)	526 (95.9854%)	151 (92.0732%)
Incorrectly Classified Instances	24 (4.562%)	22 (4.0146%)	13 (7.9268%)
Kappa statistic	0.9137	0.9247	0.8544
Mean absolute error	0.0392	0.0313	0.0676
Root mean squared error	0.1198	0.1084	0.1814
Relative absolute error	11.0018%	8.7841%	18.8351%
Root relative squared error	28.3965%	25.3986%	42.5118%
Total Number of Instances	548		164
Detailed Accuracy By Class (Weighted Avg.)	**5-fold Cross-validation**	**10-fold Cross-validation**	**Percentage Split (70%:30%)**
TP Rate	0.954	0.960	0.921
FP Rate	0.032	0.020	0.059
Precision	0.954	0.960	0.926
Recall	0.954	0.960	0.921
F-Measure	0.954	0.960	0.922
MCC	0.928	0.941	0.86
ROC Area	0.999	0.999	0.993
PRC Area	0.995	0.996	0.990
Class	high/low/ave		

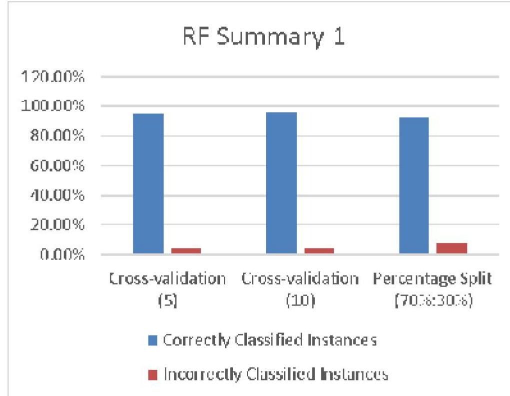

Figure 8: RF Test Options Results Visual Representation

For C4.5 and RF, all Test Options did surpassing results for each classifier. C4.5 to PS of 70%:30% showed 83.54%; 5-fold CV showed 91.97%, while 10-fold CV showed an impressive 93.7%, which revealed that all TO applied to C4.5 gave competitive returns. Last but worth saying, Random Forest. RF to PS of 70%:30% showed 92.07%, 5-fold CV showed 95.44%, while 10-fold CV showed the most with 95.99% accuracy.

Each classifier had its produced accuracy, which is shown in Figure 9, but all of them proved excellent accuracy on 10-fold Cross-validation. From it, RF to 10-fold CV made the best.

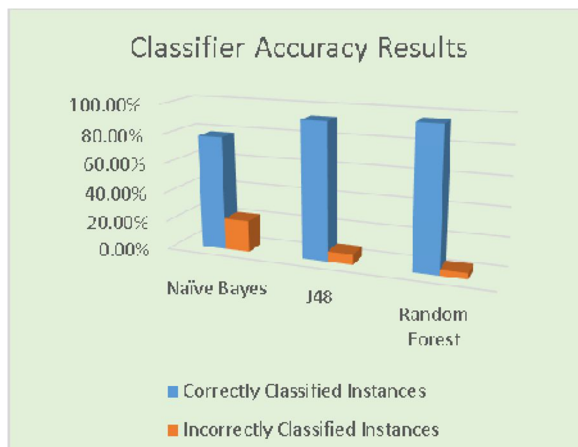

Figure 9: Classifier Accuracy Results from Visualization of NB, C4.5, and RF

```
=== Attribute Selection on all input data ===

Search Method:
        Attribute ranking.

Attribute Evaluator (supervised, Class (nominal): 12 Practicum Evaluation-0.6%=100%):
        Gain Ratio feature evaluator

Ranked attributes:
 0.2368   5 SHS Strand (ICT)
 0.1394  11 Paper & Pen Evaluation-0.4%=100%
 0.1363  10 Q, A, CP, & Pr=100%
 0.0917   7 Owned Personal Unit
 0.091    9 Class Attendance %
 0.0908   4 K-12 Grad
 0.0698   8 Course Subject Retaker
 0.0629   3 Type of Learner
 0.0324   1 Age
 0.0276   2 Gender
 0.0152   6 Resource Availability %

Selected attributes: 5,11,10,7,9,4,8,3,1,2,6 : 11
```

Figure 10: RF as the Classifier with the Most Accuracy Attribute Ranking

Upon knowing the classifier with the most accuracy, the question about whether which attribute ranked highest in influence. It revealed that with RF's to 10-fold CV, the 5 SHS Strand (ICT) attribute has the most impact in having a higher probability of nailing practical or laboratory examination that is shown in Figure 10.

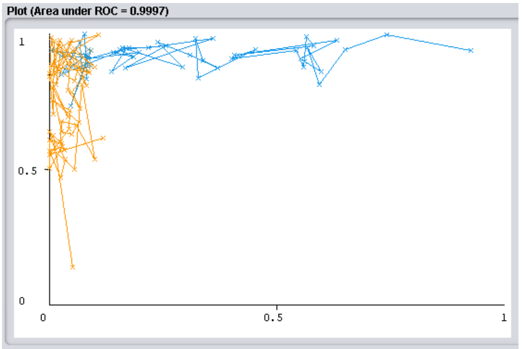

Figure 11: RF as the Classifier with the Most Accuracy Threshold Curve Visualization (Value Class=High)

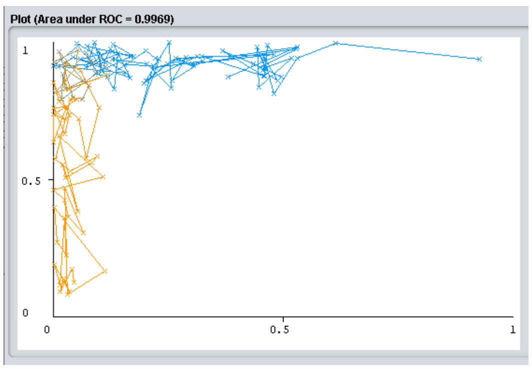

Figure 12: RF as the Classifier with the Most Accuracy Threshold Curve Visualization (Value Class=Ave)

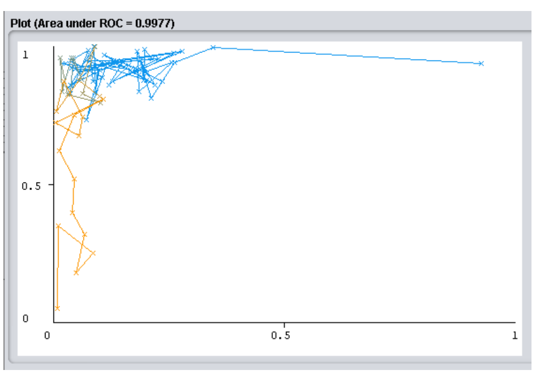

Figure 13: RF as the Classifier with the Most Accuracy Threshold Curve Visualization (Value Class=Low)

Figures 11, 12, and 13 showed that the result values of Plot (Area under Receiving Operating Characteristics [27] or ROC) of all classes (High, Ave, and Low) are close to 1, which means good in terms of measure and performance as per [30].

5. CONCLUSION

Throughout the times [27], typically, one of the greatest works in Educational Data Mining is foretelling student academic production [14], [30]. In this study, classification methods were applied in predicting the student record dataset of 549. This study is to anticipate and interpret the likelihood of a student [16] to pass a hands-on examination (laboratory) given with the implementation of OBE teaching-learning methodology.

After data selection, preprocessing, transformation, mining, and evaluation that resulted to an impressive knowledge, the most algorithm that gave a highly satisfactory result is the Random Forest with an accuracy of 95.99% — followed by C4.5 with an accuracy result of 93.07% — and Naive Bayes with an accuracy result of 78.1%.

In conclusion, the study met the goal of evaluating student's performance with the noble application of three (3) selected WEKA-based classifiers [14]. Furthermore, additional research applying different popular prediction algorithms and DM methods, or a hybrid, to evaluate the student and assessment performance [27].

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