Early Prediction of Electronics Engineering Licensure Examination Performance using Random Forest

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***Abstract*—Graduate's success on licensure examinations has a significant impact on various facets of a higher educational institution. Using a comprehensive data mining process, this research compared the accuracy of multiple classification algorithms to determine predictors of students' professional certification performance. The Random Forest model achieved the best cross-validated accuracy score of 92.70% based on the evaluation data. A model inspection method of permutation feature importance was used to uncover information from 500 graduates of Southern Luzon State University's electronics engineering program from 2014 to 2019. Among the 33 variables examined, the verbal reasoning or reading comprehension ability of students unveils a clear attribution with their licensure test results along with ratings from different courses in mathematics, professional, and electrical circuits. Thus, the data-driven information can be used to develop programs, initiatives, and techniques to improve success on the electronics engineering licensure examinations.**

Keywords*— *classification, electronics engineering, licensure examination, principal component analysis, random forest, permutation feature importance

I. Introduction

Professionals who are certified receive more than their unlicensed counterparts. They enjoy economic advantages in terms of salaries, benefits, and tenure. Higher educational institutions (HEIs) are instrumental in developing graduates with the ability, experience, and skills necessary to succeed in increasingly competitive labor markets. To face the challenges, they must prepare learners for licensure examination – a prerequisite for professional practice in many countries.

Performance on these tests serves as a standard indicator of quality education among tertiary schools – student's success on these assessments associates with instruction and curriculum design effectiveness. In addition, HEIs used the results to recruit applicants, improve the stature of the training program and alter admission policies. Universities and colleges ranking also rely on this criterion for budgetary allocations, accreditation levels, and sustainability evaluations. With high stakes and a significant impact on various facets of institutions, it is critical to recognize students at risk of failing the exams. The Professional Regulation Commission (PRC) oversees the exercise of various professions in the Philippines. It conducts examinations to measure standard knowledge, competence, and proficiency to practice as professionals. According to Republic Act 5734 of the Philippines (Electronics & Communications Engineering), it is a legal necessity to pass the tests in the specialized field concerned with the design and development of electronics and communications. Production of electronics is surging worldwide with 'Industry 4.0'. It is imperative to meet the rising demands for a qualified workforce.

Based on historical data, performances in ECE certifications have a dismal 41.26% national passing rate for the last six years. This trend of poor outcomes is an issue and concern that needs immediate attention among HEIs offering the curriculum. Southern Luzon State University (SLSU) aims to provide a quality education through up-to-date instructions, capable faculty, modern laboratory facilities, and supportive administration. One of its programs is the ECE that requires innovative thinking, good mathematical aptitude, and analytical skills.

It has observed a downward trend in its licensure performance over the last few years. As an intervention, its faculty conducted extensive review classes and coaching to solve a low passing percentage of its graduates, but Table 1 shows it is inefficient. Overall, records depict a mean of 41.54% performance, with nine times out of twelve instances below the 50% standards.

Decreasing successful examinees had been observed in other professions as well. To resolve the predicament, researchers analyzed predictors to improve licensure outcomes. The works of [1-6] identified college grade point average (GPA) as a significant variable for nursing licensing exams. These studies were in congruence to the investigations on the licensing assessments for teachers [7-15], pharmacists [16], accountants [17], agriculturists [18], and seafarers [19], while the paper of [20-21] revealed contrasting findings.

Board examination review classes' results were considered [3] [12] [19] [22-25] [34] [38], however, conclusion of [26] refutes the assertion. In addition, it regarded high school grades as a factor in determining a learner's licensure exam performance [1] [22], but evaluation by [27-29] revealed the criterion's unreliability due to school-level variations in grading standards.

Educational experts regard admission scores instead as a credible metric affecting college rating and professional

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TABLE I
SLSU ECE LICENSURE EXAMINATION PERFORMANCE AND NATIONAL PASSING RATE

Year	Month	National Passing (%)	SLSU Passing (%)	Difference (%)
2014	March	35.23	33.33	-1.90
	September	31.58	30.61	-0.97
2015	April	34.95	**51.72**	16.77
	October	34.94	29.70	-5.24
2016	April	36.95	**53.85**	16.90
	October	40.36	32.84	-7.52
2017	April	41.27	**50.00**	8.73
	October	46.72	47.30	0.58
2018	April	45.36	46.15	0.79
	October	49.49	38.37	-11.12
2019	April	48.92	40.00	-8.92
	October	49.42	44.68	-4.74

examination outcomes [1-3] [29-32] as these are unbiased baselines. Furthermore, some studies hypothesized that secondary causes such as learner study patterns [16] [17], student-faculty ratio [33], faculty academic qualifications [3] [7] [35], admission & retention policies [35], internship experiences [36] [37], and professional courses [39] [40] with inconsistencies as predictors. Published reports are very encouraging but limited. For instance, predictions are created later in a student's training – time is already insufficient to remediate their weakness. There are unlimited supplies of variables that are predictors for success in the license tests. For it to be useful, it must be known early.

Most approaches found in the literature used linear regression models, simple correlations as the core analysis, and utilized small sampling. It works well when a dataset has a definite relationship between variables but performs poorly in capturing more complex patterns. In fact, the method is sensitive to outliers, prone to noise, susceptible to overfitting, and unstable with imbalanced data. Due to its limitations, it is not recommended for most predictions as it oversimplifies solutions – real-world problems are not linear in nature. For their high accuracies in actual practice, robust data mining algorithms such as supervised learning are favored [41]. They are scalable [42] and capable of dealing with dynamic non-linear relationships [43].

As of this date, there are few articles on the predictability of electronics engineering licensure examinations. To address the gap, this paper aims to discover hidden patterns that could forecast licensure outcomes during the early stages of a student's academic life. Well-timed interventions are necessary to help them become licensed professionals.

II. METHODOLOGY

The Knowledge Discovery in Databases (KDD) approach was applied to extract unknown information from data. It is comprised of diverse techniques such as selection, preprocessing, transformation, feature selection, pattern discovery, and evaluation [44]. The research made use of a variety of statistical (*numpy & pandas*), machine learning (*scikit-learn & eli5*), visualization libraries (*matplotlib*), as well as the Python programming language for the analysis. Succeeding sections discusses each implementation.

A. Data Selection and Preprocessing

The research respondents were five hundred (500) electronics engineering graduates of SLSU from 2014 to 2019 who have taken the exams. Coverage years were selected as the same curriculum was used during those periods – this sets a consistent baseline. According to PRC documents, two hundred forty (240) passed, and two hundred (260) failed the examinations, resulting in a well-balanced dataset. A proportional sample distribution is advantageous for classification models because it prevents extreme biases [45]. The college's record section was accessed to extract course ratings, pre-admission marks, and student-related criteria. Last semester course ratings of students before graduation were excluded as the study's goal was an early prediction. Since there are no missing values, data imputation is not needed.

B. Data Transformation

Accurate machine learning models necessitate that their input is numerical; hence categorical features must be converted. Table 2 shows the attributes, values, and encoding, while Table 3 describes the SLSU's numeric grading system.

C. Feature Selection

With 33 variables on the dataset, prediction complexity increases, and generalization capability decreases. Thus, there is a need for dimensionality reduction to identify relevant features. Smaller data are easier to visualize, and machine learning algorithms train faster because fewer variables are considered. The trick is to accept a loss of precision in exchange for model simplicity. Principal component analysis (PCA), an unsupervised method, was used to derive information from large-dimensional data into a smaller subset while maintaining the maximum amount of information necessary [46]. Standardization is a critical step before PCA because it is sensitive to variances. Extreme differences between ranges mean that variables with more extensive ranges will dominate smaller ones.

The objective is to rescale in such a way that they all contribute equally to the analysis. Equation 1 summarizes the formula where x denotes the variable value, μ for the mean and σ is the standard deviation. Table 4 and Table 5 show excerpts of both data.

$$Z = \frac{x - \mu}{\sigma} \tag{1}$$

The next task is to determine the principal components through weighted variances (eigenvalues). It reduces dimensionality by discarding components with low information. Table 6 shows the values.

TABLE 2
ATTRIBUTES, VALUES AND ENCODING

Cluster	Attribute	Description	Values	Encoding
MATH COURSES	ALGEBRA	Algebra	1.00, 1.25, 1.50, 1.75, 2.00, 2.25, 2.50, 2.75, 3.00	[No Encoding]
	TRIGO	Trigonometry		
	ADVALG	Advanced Algebra		
	ANAGEO	Analytic Geometry		
	DIFCAL	Differential Calculus		
	STATS	Statistics		
	INTCAL	Integral Calculus		
	ADVMAT	Advanced Engg. Mathematics		
	NUMERIC	Numerical Methods		
	MATAVERAGE	Average Rating of Math Courses		
PROFESSIONAL COURSES	VECTOR	Vector Analysis	1.00, 1.25, 1.50, 1.75, 2.00, 2.25, 2.50, 2.75, 3.00	[No Encoding]
	ELXDEVICE	Electronics Devices & Circuits		
	ELXCIRC	Electronics Circuits & Analysis Design		
	SIGNALS	Signals and Spectra		
	PRINCO	Principles of Communication		
	LCST	Logic Circuit & Switching Theory		
	DIGICOM	Digital Communications		
	TRANS	Transmission Media		
	MICRO	Microprocessor		
	BROADCAST	Broadcast & Acoustics		
	CONTROL	Feedback & Control System		
	ECEAVERAGE	Average Rating of Prof. Courses		
ELECTRICAL CIRCUIT COURSES	CIRC1	Circuits 1	1.00, 1.25, 1.50, 1.75, 2.00, 2.25, 2.50, 2.75, 3.00	[No Encoding]
	ELEMAG	Electromagnetics		
	CIRC2	Circuits 2		
	ELEAVERAGE	Average Rating of Circuits Courses		
PRE-ADMISSION RATING	VA	Verbal Ability	AA (Above Average) AA (Average) BA (Below Average)	1 = AA 2 = A 3 = BA
	VR	Verbal Reasoning		
	FR	Figurative Reasoning		
	QR	Quantitative Reasoning		
STUDENT RELATED VARIABLES	SCHEME	Economic status of student based on Socialized Tuition Fees (per unit)	C (300 PHP) B (200 PHP) A (100 PHP)	1 = C 2 = B 3 = A
	ON_TIME	If a student is projected to complete the curriculum within the required prescribed years	YES, NO	1 = YES 2 = NO
	POTENTIAL_HONOR	If a student's GPA is greater than or equal to 1.75 before the last semester of graduation	YES, NO	1 = YES 2 = NO
CLASS LABEL	PASSER	If a student passed the licensure exams.	YES, NO	1 = YES 2 = NO

TABLE 3
SLSU'S NUMERIC GRADING SYSTEM

Grade Point	Equivalent (%)	Description
1.00	98 – 100	Excellent
1.25	95 – 97	Superior
1.50	92 -94	Very Good
1.75	89 – 91	
2.00	86 – 88	Good
2.25	83 – 85	
2.50	79 – 82	Satisfactory
2.75	76 – 78	Fair
3.00	75	Pass

TABLE 4
EXCERPT OF ORIGINAL DATA

ALGEBRA	TRIGO	ADVALG	ANAGEO	DIFCAL
3.00	3.00	2.75	2.25	3.00
2.75	3.00	3.00	3.00	3.00
1.50	1.50	1.25	1.25	1.75
2.25	2.50	2.25	3.00	2.25

TABLE 5
EXCERPT OF STANDARDIZED DATA

ALGEBRA	TRIGO	ADVALG	ANAGEO	DIFCAL
1.211	1.003	0.609	-0.282	0.816
0.735	1.003	1.095	1.051	0.816
-1.642	-1.956	-2.301	-2.060	-1.796
-0.215	0.016	-0.360	1.051	-0.751

TABLE 6
PRINCIPAL COMPONENTS

Attribute	PC1	PC2	PC3	PC4
ECEAVERAGE	**0.429**	0.046	0.024	0.042
MATAVERAGE	**0.420**	0.116	0.082	0.031
ELEAVERAGE	**0.418**	0.160	0.006	0.082
SIGNALS	0.207	0.134	0.030	0.063
ELXDEVICE	0.203	0.171	0.029	0.001
CIRC1	0.202	0.027	0.079	0.206
ELEMAG	0.199	0.205	0.075	0.083
ELXCIRC	0.197	0.015	0.032	0.064
TRIGO	0.197	0.072	0.049	0.013
CONTROL	0.195	0.012	0.149	0.221
DIFEQU	0.188	0.027	0.055	0.147
ALGEBRA	0.185	0.046	0.024	0.026
DIFCAL	0.184	0.243	0.105	0.019
PRINCO	0.184	0.202	0.197	0.161
ANAGEO	0.184	0.196	0.124	0.090
ADVALG	0.183	0.235	0.160	0.001
TRANS	0.181	0.139	0.284	0.131
INTCAL	0.179	0.082	0.029	0.099
BROADCAST	0.177	0.069	0.178	0.100
LCST	0.175	0.177	0.040	0.189
MICRO	0.174	0.043	0.193	0.207
DIGICOM	0.170	0.151	0.115	0.257
CIRC2	0.165	0.239	0.174	0.099
VR	0.152	**0.402**	0.066	0.075
ADVMAT	0.151	0.108	0.214	0.246
STATS	0.146	0.357	0.026	0.172
VECTOR	0.145	0.320	0.340	0.274

The explained variance ratio is used for principal component (PC) selections – a percentage statistic that shows a component's usefulness when constructing a model. Ideally, a cumulative value of 70% or better is recommended to avoid overfitting [48]. Based on Figure 1, a total of 93.14% variances are contained within two components – PC1 (80.20%) and PC2 (12.94%). Feature loadings on Table 4 revealed that ECEAVERAGE (0.429), MATAVERAGE (0.420), ELEAVERAGE (0.418), and VR (0.402) are the best attributes for each component. In the model training, these features were used.

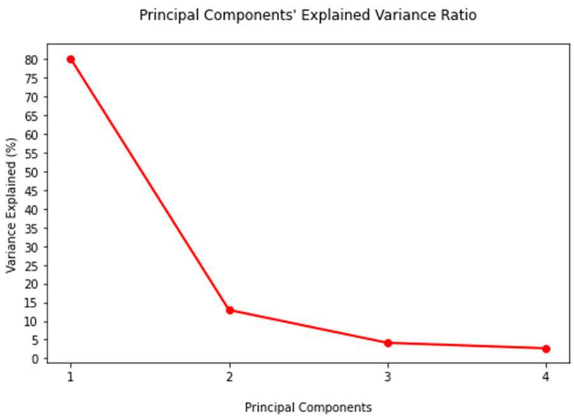

Fig. 1. Scree plot of explained variance ratios of principal components

D. Pattern Discovery

In this phase, the reduced final dataset was divided into a 70/30 stratified training and testing split. The training set refers to the samples applied to construct the model, while the test (validation) portion quantifies the performance. Logistic Regression, Naïve Bayes, Support Vector Machines, and Random Forest classification techniques were tested to discover the best approach to build the prediction model. The results obtained were evaluated and represented as new knowledge.

E. Evaluation

The evaluation is a critical stage in the implementation of machine learning algorithms. Its purpose is to uncover the best model representations of a given data and how well it can work with unseen information. Estimates of classification quality used the receiving operating characteristic (ROC) and area under the curve (AUC) plots. These are standard evaluation techniques for assessing a models' generalization capability. The traditional academic point system shown in Table 7 serves as the measurement guide.

TABLE 7
TRADITIONAL ACADEMIC POINT SYSTEM

Range	Description
0.90 – 1.00	Excellent
.80 - .90	Good
.60 - .70	Poor
0.50 - .60	Fail

III. RESULTS AND DISCUSSIONS

Table 8 compares the classification performances of different supervised machine learning algorithms in predicting licensure examination outcomes. Random Forest attained the highest cross-validated (10-fold) accuracy score of 92.70%, followed by support vector machines with 91.13%. Both Naïve Bayes and Logistic Regression obtained a 90.70% precision.

TABLE 8
PERFORMANCE RESULTS OF CLASSIFICATION ALGORITHMS

	Classification Algorithms			
Metrics	Logistic Regression	Naïve Bayes	Support Vector Machines	Random Forest
Accuracy	90.70%	90.70%	91.13%	**92.70%**
Error	9.30%	9.30%	8.87%	7.30%

A confusion matrix summarized the performance of random forests. It is a rundown of the ratio of correct and incorrect predictions that a model has made [49]. Based on Table 9, the algorithm is better at predicting unsuccessful licensure examinees than successful ones with 92% and 91% accuracies, respectively.

TABLE 9
CONFUSION MATRIX OF RANDOM FOREST

Test Size, N = 150 (30%)	Predicted: Passer (YES)	Predicted: Passer (NO)
Actual: Passer (YES)	66	6
Actual: Passer (NO)	6	72

To further evaluate the classification quality of the selected model, curve plots were generated. Figure 2 confirms that the prediction is not random as the ROC curve (green) is significantly above the guessing line (red). AUC score also confirms an 'excellent' prediction rating of 0.975.

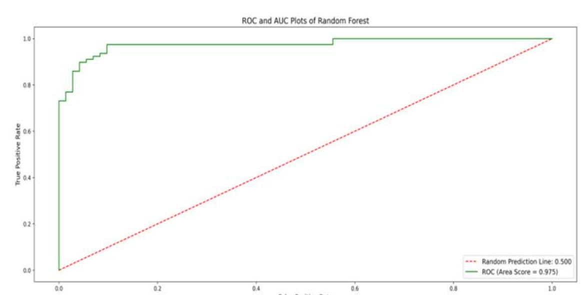

Fig. 2. ROC and AUC plots of random forest

Predictions using linear models are easy to understand, but they are inaccurate. There are trade-offs between accuracy and interpretability regarding 'black box' models, such as a random forest. It is powerful in reducing prediction errors by combining weak decision trees to construct a solid predictive ensemble, but its information is hidden inside the structure. To extract the knowledge, permutation feature importance or mean decrease accuracy (MDA) was calculated to determine each feature's contribution to the prediction [50]. A decrease in the model score through random shuffling of variable values indicates how much a model depends on a feature. Table 10 shows the feature importance through 10 random exchanges.

Based on the analysis, it revealed that student's verbal reasoning ability or reading comprehension skills (0.1187) had a significant influence on the licensure examination results, followed by mathematics (0.0893) and professional course (0.0267) ratings. The least contributor was the electrical circuit course grades (0.0093).

TABLE 10
PERMUTATION FEATURE IMPORTANCE

Weight	Feature
0.1187 ± 0.285	VR
0.0893 ± 0.272	MATAVERAGE
0.0267 ± 0.0270	ECEAVERAGE
0.0093 ± 0.0107	ELEAVERAGE

The Pearson correlation coefficient exhibited in Table 11 affirms a very strong positive relationship between verbal reasoning with passing the license tests at 0.803. In addition, courses such as mathematics (0.719), professional (0.614), and electrical circuits (0.574) also have a positive association with verbal reasoning.

TABLE 11
CORRELATION VALUES

	VR
MATAVERAGE	0.719
ECEAVERAGE	0.614
ELEAVERAGE	0.574
PASSER	**0.803**

From these results, it is clear that verbal reasoning has a strong attribution to both students' academic and licensure examination success. It is a core competence in absorbing knowledge in a scholarly setting and future careers [51]. Understandably, professional engineering tests are chiefly composed of problem-solving, primarily written in words. Based on the model, 226 (45.20%) respondents who have successfully passed the electronics engineering licensure examination have an 'above average' rating in verbal reasoning with an average mathematical rating of 2.51 or better. In addition, 14 (2.80%) takers with an 'average' rating in reading comprehension and average mathematical rating of 2.41 or better also passed the exams – a small proportion. In contrast, 223 (44.60%) graduates who failed the assessments have an 'average' rating in reading comprehension and an average mathematical rating of 2.53 or lower. Finally, 34 (6.80%) students with 'above average' reading comprehension and average mathematical rating of 2.49 or lower have also failed the examinations.

It is important to note that most students admitted to the University's engineering programs have decent quantitative or numerical reasoning skills upon entry. For most years, verbal reasoning skills have been overlooked. Student-related factors such as finishing the program on time, graduating with honors, and economic status have no significant impact on the outcomes.

The findings supports the claim of [51] [52], showing a clear substantial association between linguistic competence, such as verbal reasoning and problem-solving abilities. According to a study conducted by [53], when engineering students practiced verbal reasoning via cumulative sentence analysis, their test scores increase by 9%. Verbal reasoning competence is also associated with positive learning patterns, as the majority of learners who exhibit this trait are avid readers [54].

In a recent evaluation, the Philippines ranked the lowest among 79 countries in reading comprehension at the basic education level in 2018 [55]. Under certain assumptions, this study speculates that the root causes of poor licensure examination performance cannot be construed on the tertiary level achievement alone but on the whole education system itself.

The study's drawback is that it relies exclusively on student's academic abilities and ignores external considerations such as faculty-related, administrative-related, and environmental-related dimensions.

IV. CONCLUSIONS AND RECOMMENDATIONS

Early prediction of licensure examination performance is necessary to come up with timely interventions to increase student success. The Higher educational institution must resolve the declining national passing rate for the electronics engineering professional certification. With surging global demands for electronics due to 'Industry 4.0', they must supply a competent labor force.

This paper focuses on analyzing student-related variables using data mining techniques to create an accurate prediction model for student's licensure examination outcomes. Random Forest obtained the highest accuracy compared to other machine learning classification algorithms.

The main contribution of this paper is the knowledge discovered that offers a unique perspective that verbal reasoning skill is a key component that cannot be neglected and must be developed during a learner's scholarly life. Moreover, a combination of high ratings in verbal reasoning skills and high mathematical aptitude was found as powerful predictors of student's success. The study's findings can be used to develop policies, strategies, and interventions to assist graduates in passing the board examinations. The next step of the study would be to classify external variables that influence student performance and utilize ensemble machine learning approaches to enhance the model's accuracies.

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Early Prediction of Electronics Engineering Licensure Examination Performance using Random Forest

Publisher: IEEE

Renato Racelis Maaliw **All Authors**

Abstract:

Graduate's success on licensure examinations has a significant impact on various facets of a higher educational institution. Using a comprehensive data mining process, this research compared the accuracy of multiple classification algorithms to determine predictors of students' professional certification performance. The Random Forest model achieved the best cross-validated accuracy score of 92.70 % based on the evaluation data. A model inspection method of permutation feature importance was used to uncover information from 500 graduates of Southern Luzon State University's electronics engineering program from 2014 to 2019. Among the 33 variables examined, the verbal reasoning or reading comprehension ability of students unveils a clear attribution with their licensure test results along with ratings from different courses in mathematics, professional, and electrical circuits. Thus, the data-driven information can be used to develop programs, initiatives, and techniques to improve success on the electronics engineering licensure examinations.

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