Journal of Education, Social Sciences, and Allied Health
Volume 1, Issue 1
Journal Homepage: https://www.isujournals.ph/index.php/jessah
Publisher: Isabela State University, Echague, Isabela, Philippines

Generating Licensure Examination Performance Models Using JRip Classifier: A Data Mining Application in Civil Engineering

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RESEARCH ARTICLE INFORMATION	ABSTRACT

Received: May 26, 2023
Reviewed: June 19, 2023
Accepted: May 07, 2024
Published: June 28, 2024

The purpose of this study was to create performance models for civil engineer licensure examinations using the JRip classifier. It identified the attributes that were significant to the response attribute, generated prediction models using JRip classifiers of WEKA, and determined how likely a CE graduate pass the CE Licensure Examination. The respondents were obtained from the CE graduates of Cavite State University Indang Main Campus who took a CE board examination from November 2016 to May 2019. The results obtained indicated the significance of the subject AENG 65, as well as CENG 65B and CENG 130 in predicting the CE Licensure Examination. The CE graduates were predicted to fail if their grade of AENG 65 is greater than or equal to 3 and CENG 135 is less than or equal to 2.5, and if CENG 120A and MATH 21B are greater than or equal to 2.75 and CENG 106 is less than 1.75. It also further concluded that if DCEE27 is greater than equal to 2.5 and the CENG 22A is greater than equal to 3 and the grade of CENG 110A is less than or equal to 2.75, then the CE graduates would fail the Licensure exam.

Keywords: *JRip, WEKA, Attribute, Licensure Examination, Civil engineering*

Introduction

A professional's license is a government-issued standard mark in the general public to present excellence, norms of conduct, recruitment criteria, and member protection measures, ensuring a high level of commitment, responsibility, skills, and quality in one's career (Dayaday 2018). Engineering has transformed the world, yet it is a conservative and slow-moving profession (UNESCO 2010). Engineers play such an important part in today's world, Most countries are focusing on the concept of licensing this profession (Ferrer et al., 2015). Engineers Licensure Examination is a tool for evaluating and ensuring the quality of engineers who will work in a variety of manufacturing enterprises in the Philippines and abroad (Dizon, 2013). Licensure examination performance is among the output indicators of said normative funding system in the allocation of expenditures to state universities and colleges (SUCs), It influences part of the budget received by the institution. This is the reason why Higher Education Institutions are paying close attention to their graduates' licensure examination results (Lascano & Bansiong 2017; Tarun et al., 2014). The Cavite State University (CvSU), Indang, Cavite faced with the current situation, the school's programs, particularly those requiring board examinations, must continue to meet the growing demand for excellence since the national passing rate of Bachelor of Science in Civil Engineer (BSCE) in CvSU does not even reach 50% according to the Philippines Regulatory Commission (PRC) since 2016 to 2019. Currently, the school always strives for strong performance in board examinations in the domain of civil engineer licensure examination. Board examination reviews were done as a strategy by the department. There have been various attempts to find models for predicting licensure examination results; however, most research proposed a larger study with more independent factors and different approaches. For instance, Roehrig (1998) conducted a study to predict licensure examination performance among Physical Therapy graduates. To predict licensing exam scores, researchers used ACT scores, necessary and non-prerequisite grade point averages (GPAs), and interviews and recommendation scores (Roehrig 1988). Ong et al. (2012) used inferential approaches to determine the predictors of nursing graduates' licensure examination performance. College entrance examination intelligence test, nursing aptitude test, composite score of science, Math, and English exams, college grade point average, as well as pre-board examination performance were the variables employed.

On the other hand, Soriano (2009) focused his research on the cognitive as well as non-cognitive records of education graduates. In the confines of her study, her goal was to find the best indicators of LET success. She discovered that the respondents' LET performance was best predicted by their GPA in general education, college entry exam score, course, and gender. Thus, she recommended that a follow-up study involving other factors such as school schedule, reviews attended, Field Study evaluations, school environment, and instructor factor should be done. Other researchers used a descriptive–correlational strategy to discover the association between in-house review and LET performance (Fiscal & Roman, 2022; Amanonce & Maramag 2020; Roman, 2018). They discovered a substantial correlation between pre-board and LET outcomes. They suggested that a similar study be conducted for BEEd and BSEd content courses and fields of expertise.

The subsequent literature, on the other hand, justifies the capability of data mining methods in the prediction of student performance, which was regarded as useful in the development of the study's framework. According to Slezak et al. (2014), to predict student performance in a course utilizing social network data, his co-authors used regression and machine learning approaches utilizing the R-project software as well as WEKA, respectively. They claimed that students' final ratings are closely tied with those of their friends. They were able to show that a student's final grade is related to those of their friends using multiple linear regressions. Likewise Sembiring et al. (2011) used the kernel methods for data mining to examine correlations between student behavior and success and also to develop a model of student 's performance predictors. They concluded from their research that data mining was particularly beneficial in predicting student final performance. Hence, utilizing WEKA Explorer and data mining can reliably predict students' overall course performance (Mellalieu, 2011). He also developed a decision support system prototype, which was deployed as ReXS, an interconnected collection of spreadsheets.

Analyzing this large amount of data is a difficult task, thus having the right tools and approaches for sorting large amounts of data is critical. Data mining is one of the techniques for transforming unstructured data into useful information and knowledge (Hastie, et al., 2009). By uncovering, learning, and knowing underlying patterns, trends, and structures, data mining automatically finds and analyzes vast amounts of data (Mita et al., 1981) and provides answers to queries that cannot be answered using traditional query and reporting approaches (Ahmeda et al., 2015). This study was conducted to look into the elements that influence BSCE board exam results. In detail, the study aimed to determine (1) which predictors were significant to students' performance on the BS Civil Engineering Licensure Examination (2) what BSCE Licensure Examination prediction models could be derived from the predictors and (3) how likely would a CE graduate pass the CE Licensure Examination based on the predictors? In doing so, the study's findings would serve as a basis for the department, college, and university, helping them to place greater emphasis on, revise, and emphasize the factors that improve BSCE-CvSU graduates' performance on the board examination.

Methods

Conceptional Framework

Han and Kamber (2016) illustrated the Knowledge Discovery Process (KDP) in their textbook "Data Mining: Concepts и Techniques, Second Edition", which served as the study's framework. The KDP was altered to meet the study's aims. Figure 1 shows the modified form.

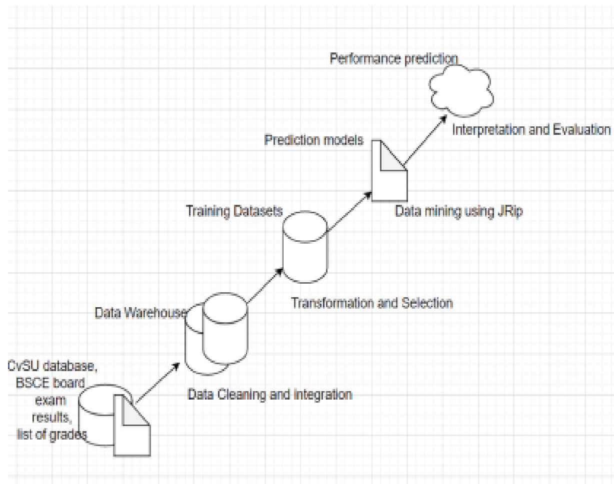

Figure 1. *Conceptual Framework*

Research Design

Experimental research design and quantitative approach were utilized since the study dealt with determining the factors affecting the performance in Civil Engineering Licensure Examination and which predictors were significant to students' performance. An experimental design improves a researcher's capacity to establish causal relationships and draw causal conclusions by using accurate and accurate empirical measurement and control (Bell, 2009). Statistical approaches enabled the researcher to better understand and analyze the factors that influenced a certain subject using experimental design procedures. Such methods combine theoretical understanding of experimental designs with practical knowledge of the factors to be investigated (Hanrahan et al., 2004).

Research Participants

The participants in this study were BSCE graduates at CvSU Indang in Cavite, Philippines, who took the BSCE Licensure Examination between November 2016 and May 2019. The study only looked at first-time takers. Enumeration in its entirety was used. The study included 156 participants.

Data Description

The PRC provided the ratings of all BSCE board examinees who passed and failed the exam, while the Registrar's Office or the Department of Computer and Electronic Engineering (DCEE) provided the list of grades and computed weighted average for all subjects.

Research Procedure

Permission was obtained from the relevant academic department prior to data collection. In order to meet ethical guidelines, the database administrators anonymized each student's academic records. After that, the co-author received the anonymized data. It was impossible to create any kind of bond with anyone because of this. Concerns about admission criteria and access to student admittance information were handled by senior academicians as well as top university authorities. There was an internal system for cross-checking the grades given to each student for every subject.

Data Analysis

Duplicate records were removed from the data that was contained in various tables. Similarly, records with empty values were removed. The researchers used JRip of WEKA, which is a classification algorithm, to generate models. In WEKA, applying the best classifier JRip to the dataset attribute evaluation was done first. The purpose of the attribute evaluation was to find attributes that were significant to the response variable, which was the BSEE licensure performance. Figure 1 shows the distribution of data for all attributes.

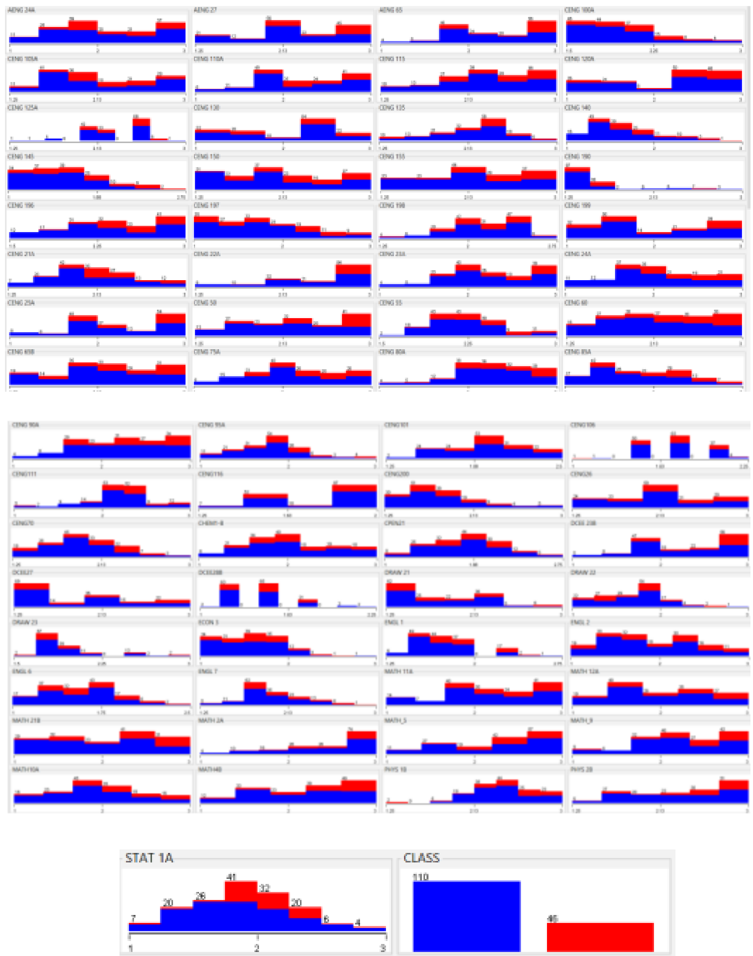

Figure 1. *Visualization of All Attributes*

Ethical Considerations

Before commencing the gathering of data, the research team secured authorization from the proper academic department to proceed with their study. This measure was taken to ensure that all research activities were carried out in accordance with applicable rules and ethical guidelines. The database administrators went above and beyond to anonymize the data in order to protect the privacy and confidentiality of each student's academic records. After the anonymization process was done, the co-author was allowed access to the data, allowing them to conduct their research in a responsible and respectful manner, taking into consideration the rights and privacy of all individuals involved.

Results and Discussion

The Attribute and Their Values

These data, which were kept in various tables, were cleansed by getting rid of duplicate records Similarly, records with empty values were removed. The researchers combined the data from the many tables into a single data warehouse, where it was processed into meaningful clusters within the attributes to fulfill the study's goals. Table 1 shows the predictor and response attributes that they derived.

Table 1. Attributes and Their Values

Attributes	Discription	Value
AENG 24A	Environmental Engineering	1-5
AENG 27	Methods of Research with Experimental Design	1-5
AENG 65	Hydrology	1-5
CENG 100A	Earthquake Engineering	1-5
CENG 105A	Earthquake Engineering	1-5
CENG 110A	Highway Engineering	1-5
CENG 115	Timber Design	1-5
CENG 120A	Theory of Structures	1-5
CENG 125A	Construction Cost Engineering	1-5
CENG 130	Steel Design	1-5
CENG 140	Transportation Engineering	1-5
CENG 145	Water Resources Engineering	1-5
CENG 150	C E Laws, Contracts, Specifications and Ethics	1-5
CENG 155	Construction Methods and Project Management	1-5
CENG 190	Inspection Trips and Seminar	1-5
CENG 196	C E Competency Appraisal	1-5
CENG 197	C E Competency Appraisal 2	1-5
CENG 198	C E Competency Appraisal 3	1-5
CENG 199	On - The - Job Training	1-5
CENG 21A	Safety Management	1-5
CENG 22A	Statics of Rigid Bodies	1-5
CENG 23A	Dynamics of Rigid Bodies	1-5
CENG 24A	Engineering Economy	1-5
CENG 25A	Mechanics of Deformable Bodies	1-5
CENG 50	Elementary Surveying	1-5
CENG 55	Building Design	1-5
CENG 60	Higher Surveying	1-5
CENG 65B	Building system design	1-5
CENG 75A	Geotechnical Engineering 1(Soil mech.)	1-5
CENG 80A	Hydraulics	1-5
CENG 85A	Route surveying	1-5
CENG 90A	Theory of structures	1-5
CENG 95A	Building design 2	1-5
CENG101	Bridge Engineering	1-5
CENG106	Highway Design and traffic safety	1-5
CENG111	Pre-stressed conrete design	1-5
CENG116	Special topics in structural engineering	1-5
CENG200	C E Project	1-5
CENG26	Engineering Management	1-5
CENG70	Construction materials and testing	1-5
CHEM1-B	General chemistry	1-5
CPEN21	Fundamentals of computer programming	1-5
DCEE 23B	Advanced engineering math for CE	1-5
DCEE27	Basic Electrical Engineering	1-5
DCEE28B	Basic Mechanical Engineering	1-5
DRAW 21	Engineering drawing 1	1-5
DRAW 22	Engineering drawing 2	1-5
DRAW 23	Computer aided drafting and design (cadd)	1-5
ECON 3	General economics with l r t	1-5
ENGL 1	Study and thinking skills in english	1-5
ENGL 2	Writing in the discipline	1-5
ENGL 6	Speech communication	1-5
ENGL 7	Scientific reporting / thesis writing	1-5
MATH 11A	Integral calculus	1-5
MATH 12A	Differential equations	1-5
MATH 21B	Snalytic geometry	1-5
MATH 2A	College algebra	1-5
MATH_5	Advanced algebra	1-5
MATH_9	Numerical analysis	1-5
MATH10A	Differential calculus	1-5
MATH4B	Plane trigonometry	1-5
PHYS 1B	Mechanics and thermodynamics	1-5
PHYS 2B	General physics 2	1-5

Classification Method Used

STAT 1A	Engineering probability and statistics	1-5
BSCE LE Performance	This is the BSCE performance on licensure exam which makes use of 2 classes	Passed, Failed

The researchers used JRip of WEKA. It uses sequential covering algorithms to create ordered rule lists and uses a propositional rule learner dubbed "Repeated Incremental Pruning to Produce Error Reduction (RIPPER)." Growing a rule, pruning, optimization, and selection are all stages of the algorithm (Gupta et al., 2016; Veeralakshmi, 2015). The algorithm performs cross-validation of the eight (8) folds including a set of attributes and the related outcome, commonly referred to as the target or prediction attribute, in order to predict the outcome of the datasets. The accuracy of JRip is 78.2051% which is the best classifier shown in Figure 2.

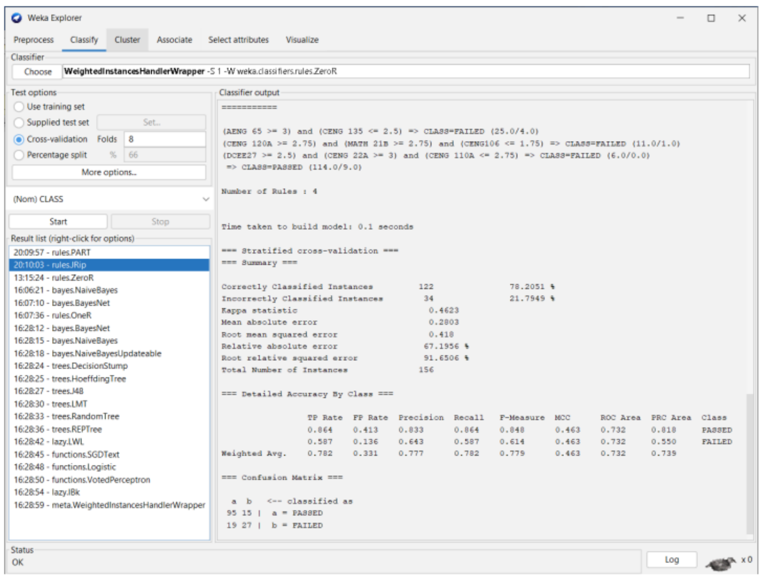

Figure 2: *JRip Percentage of Accuracy*

Attribute Evaluation

ClassifierAttributeEval with the search method of Ranker was used to determine the rank of the subject who had the most impact in CE Licensure Examination. As seen in Figure 3, the AENG 65 followed by CENG 65B to CENG 130 were the top 20 subjects that had the most impact in CE Licensure Examination. However, all of the predictors were kept in the dataset because they may be required for a certain occurrence. Kovacic (2010) had a similar experience, where despite their insignificance found during feature selection, all available predictors in his dataset were used in the classification tree analysis.

```
=== Attribute selection 8 fold cross-validation (stratified), seed: 1 ===

average merit       average rank  attribute
 0.096 +- 0.013       1    +- 0        3 AENG 65
 0.045 +- 0.01        3    +- 0.71    29 CENG 65B
 0.027 +- 0.017       9.6 +-12.73     16 CENG 190
 0.021 +- 0.018       9.8 +- 6.08      2 AENG 27
 0.038 +- 0.027       9.9 +-17.84     26 CENG 50
 0.016 +- 0.012      11.3 +- 9.48     41 CENG70
 0.018 +- 0.022      14.6 +-14.78     13 CENG 145
 0.014 +- 0.018      14.6 +-14.82     27 CENG 55
 0     +- 0          15.9 +- 4.28     36 CENG106
 0     +- 0          16.3 +- 3.38     35 CENG101
 0.004 +- 0.014      18.6 +-17.04     28 CENG 60
-0.002 +- 0.003      20.5 +- 8.69     39 CENG200
 0.007 +- 0.019      20.6 +-19.26     51 ENGL 1
-0.002 +- 0.003      21.3 +-10.65     37 CENG111
 0.011 +- 0.03       21.8 +-22.9      57 MATH 21B
 0     +- 0          22.1 +- 8.64     42 CHEM1-B
-0.003 +- 0.005      22.1 +- 9.73     38 CENG116
-0.001 +- 0.004      23.6 +- 5.59      8 CENG 120A
 0     +- 0          23.9 +- 5.11     19 CENG 198
 0     +- 0          24.5 +- 3.64     10 CENG 130
-0.002 +- 0.004      25.3 +-10.77     43 CPEN21
-0.004 +- 0.008      27   +-12.28      7 CENG 115
-0.005 +- 0.009      27.1 +-13.15     22 CENG 22A
 0     +- 0          27.1 +- 5.18     46 DCEE28B
-0.003 +- 0.009      27.9 +-12.77     33 CENG 90A
 0     +- 0          28.1 +- 2.37     58 MATH 2A
-0.008 +- 0.009      29.3 +-14.8      64 PHYS 2B
 0     +- 0          29.4 +- 4.06     49 DRAW 23
-0.003 +- 0.008      29.9 +-10.04      1 AENG 24A
-0.007 +- 0.012      30.4 +-14.39     40 CENG26
-0.007 +- 0.01       30.6 +-15.7      65 STAT 1A
-0.008 +- 0.01       30.9 +-16.54     23 CENG 23A
-0.005 +- 0.006      31.5 +- 9.72      9 CENG 125A
-0.004 +- 0.003      32.5 +- 2.87     50 ECON 3
-0.008 +- 0.012      34   +-12.64     60 MATH_9
-0.012 +- 0.011      35   +-17.48     25 CENG 25A
-0.007 +- 0.017      36.4 +-14.2      54 ENGL 7
-0.013 +- 0.025      36.9 +-22.62     44 DCEE 23B
-0.011 +- 0.008      38.8 +-11.05     47 DRAW 21
-0.012 +- 0.012      39.9 +-12.61     59 MATH_5
-0.017 +- 0.022      40   +-20.17     21 CENG 21A
-0.012 +- 0.006      40.3 +- 5.95     11 CENG 135
-0.015 +- 0.01       40.5 +-13.54     30 CENG 75A
-0.014 +- 0.018      41.9 +-16.68     55 MATH 11A
-0.015 +- 0.005      42.8 +- 6.02     61 MATH10A
-0.016 +- 0.016      42.9 +-17.95     31 CENG 80A
-0.017 +- 0.014      43.3 +-15.63     24 CENG 24A
-0.022 +- 0.021      43.9 +-21.05     15 CENG 155
-0.022 +- 0.019      44.5 +-18.63      5 CENG 105A
-0.017 +- 0.012      45.1 +-13.28     56 MATH 12A
-0.018 +- 0.006      46.4 +- 4.77     18 CENG 197
-0.027 +- 0.022      48   +-21.97      6 CENG 110A
-0.022 +- 0.012      48.4 +-11.79     53 ENGL 6
-0.019 +- 0.01       48.9 +- 9.16     63 PHYS 1B
-0.023 +- 0.011      50.1 +- 9.96     45 DCEE27
-0.024 +- 0.011      50.3 +- 8.58      4 CENG 100A
-0.022 +- 0.007      50.3 +- 6.67     52 ENGL 2
-0.022 +- 0.012      50.3 +- 9.47     32 CENG 85A
-0.023 +- 0.007      51   +- 7.62     12 CENG 140
-0.025 +- 0.013      51   +-10.56     14 CENG 150
-0.025 +- 0.012      51.4 +- 9.56     48 DRAW 22
-0.026 +- 0.011      52.3 +- 9.4      17 CENG 196
-0.028 +- 0.011      54.4 +- 8.11     20 CENG 199
-0.027 +- 0.007      54.9 +- 6.01     34 CENG 95A
-0.036 +- 0.009      60   +- 5.1      62 MATH4B
```

Figure 3. *Attribute Evaluation*

JRip Prediction Model

JRip is a RIPPER-based inference as well as a rule-based learner that aims to provide propositional rules for classifying components (Hindle et al., 2009). Figure 4 shows the prediction model created by JRip utilizing WEKA in an 8-fold cross-validation. The following are the four rules:

If AENG 65 is greater than or equal to 3 and CENG 135 is less than or equal to 2.5, the CE graduates would likely fail the CE Licensure Examination.

If CENG 120A and MATH 21B are greater than or equal to 2.75 and CENG 106 is less than 1.75, the CE graduates would likely fail the CE Licensure Examination.

If DCEE27 is greater than or equal to 2.5 and CENG 22A is greater than or equal to 3 and CENG 110A is less than or equal to 2.75, the CE graduates would likely fail the CE Licensure Examination. Otherwise, the CE graduates are predicted to pass the CE Licensure Examination.

```
JRIP rules:
===========

(AENG 65 >= 3) and (CENG 135 <= 2.5) => CLASS=FAILED (25.0/4.0)
(CENG 120A >= 2.75) and (MATH 21B >= 2.75) and (CENG106 <= 1.75) => CLASS=FAILED (11.0/1.0)
(DCEE27 >= 2.5) and (CENG 22A >= 3) and (CENG 110A <= 2.75) => CLASS=FAILED (6.0/0.0)
 => CLASS=PASSED (114.0/9.0)

Number of Rules : 4
```

Figure 4. *JRip Rules*

JRip Confusion Matrix

The overall percentage of correct classification of JRip is 78.21% as shown in Figure 5. There are only 34 incorrectly classified instances, which indicates that the model is incorrect for only 29.79% of the cases in the dataset.

```
=== Confusion Matrix ===

  a  b   <-- classified as
 95 15 |  a = PASSED
 19 27 |  b = FAILED
```

Figure 5. *Confusion Matrix*

Conclusion and Future Works

In light of the results, the researchers concluded that the subject AENG 65, as well as CENG 65B through CENG 130 in the Figure 3 attribute evaluation, were significant to the response attribute, which was CE performance in the licensure examination. This was based on the results obtained in attribute selection. As for the prediction model obtained using the JRip classifier, it can be concluded that if the grade in AENG 65 is greater than or equal to 3 and the grade in CENG 135 is less than or equal to 2.5, the CE graduates would likely fail the CE Licensure Examination. In addition, if their grades in CENG 120A and MATH 21B are greater than or equal to 2.75 and their grade in CENG 106 is less than 1.75, the CE graduates would likely fail the CE Licensure Examination. It can also be concluded that if their grade in DCEE27 is greater than or equal to 2.5, while their grade in CENG 22A is greater than or equal to 3, and their grade in CENG 110A is less than or equal to 2.75, the CE graduates would likely fail the CE Licensure Examination. Other than these specified rules, the CE graduates are predicted to pass the Licensure examination. These models can be of help to civil engineers as they identify students who need special review assistance in specific subjects and eventually increase the licensure exam passing rate.

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Acknowledgment

The researchers would like to thank the Cavite State University-Main Campus for the continued support in providing the needed data.