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Machine Learning Ecosystem to Enhance Grade Point Average

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Abstract This study aims to 1) develop Machine Learning Ecosystem models to enhance grade point averages, and 2) predict grade point averages by modeling Machine Learning Ecosystem techniques, namely, Decision Trees (DT), Naïve Bayes (NB), and a Neural Network (NN). Findings from an efficiency comparison of the three models of a Machine Learning Ecosystem in predicting grade point averages showed that DT achieved the highest accuracy of 100.00%. In contrast, NN achieved the second-highest accuracy of 85.83%, and NB achieved the lowest accuracy of 81.67%. For the F-Measure, the F-Measure with DT, NN, and NB was 100.00%, 76.59%, and 70.59%, respectively. Thus, DT was the most appropriate model for a Machine Learning Ecosystem to predict the students' GPA.

Keywords Learning Ecosystem, Machine Learning, Grade Point Average, Decision Tree, Naïve Bayes, Neural Network

1. Introduction

Nowadays, each year brings new university graduates, and many of them are unable to find employment due to the coronavirus COVID-19 pandemic and the increasing use of new technologies by entrepreneurs. Therefore, a grade point average (GPA) has become essential for graduates. It is undeniable that GPA is the first thing that employers consider and use to judge students. It can indicate the responsibility, attention, and commitment of a graduate's study at university. Due to the importance of GPA, high grades in courses, especially the fundamental and mandatory courses of a curriculum, can be significant factors resulting in a graduate's GPA. Furthermore, the management of the learning and teaching environment also significantly impacts grades since each student may be successful due to different environments. As a result, a learning ecosystem positively affects students' learning and comprises interactions between learners and content, technologies, and surrounding information [1]. Another method used to develop GPA is machine learning, as it is used as a brain of artificial intelligence [2]. It can be utilized, for example, for classification, prediction, and the improvement of GPA in the future [3]. Due to the importance of GPA as mentioned above, the researchers studied and used a concept of the learning ecosystem and machine learning to enhance the undergraduates' GPA and proposed that the three predictive machine learning techniques: DT, NB, and NN, can predict GPA resulting from managing the learning ecosystem to develop and improve the GPAs. Therefore, due to the importance of GPA and machine learning techniques, the researchers presented the concept of enhanced GPA to explore factors that affect the development of students' GPA levels. These include educational institutions or courses to develop learning environments, and course instructors who had a special effect and enhanced GPA compared to other courses.

This paper consists of seven sections as follows:

Section 1 Introduction; Section 2 Literature Review; Section 3 Methods; Section 4 Result; and Section 5 Conclusion.

2. Literature Review

The following are relevant studies from a review of documents and related research on Machine Learning Ecosystem models used to enhance the grade point average.

2.1. Learning Ecosystem

A learning ecosystem is defined from the theory of a learning ecosystem. It states that a learning ecosystem refers to promoting technology as a crucial part of constructing cooperation in a class by both learners and teachers [4]. It is also defined as developing learners' learning by designing and developing a learning environment that includes classrooms of an educational institution and other related areas outside the educational institution [5]. According to [6], it refers to constructing relations of existing things consisting of biotic or living organisms and abiotic or non-living organisms in an ecosystem, including all physical components in environments where there are interactions between these biotic things. Moreover, it maintains that the learning ecosystem studies the rules of teaching development in society [7]. It uses ecological methods that emphasize the balance of an ecosystem, environment and adjustment, distribution and components of the population, relations, and other related issues to create suitable ecological environments for schools to improve teaching effectiveness.

Therefore, the learning ecosystem is a construction of relations of things in an ecosystem using technology to design practical teaching and learning for learners to achieve their academic goals.

2.1.1. Components of the learning ecosystem

From previous studies, the components of the learning ecosystem can be defined variously. According to [4], the components of the learning ecosystem consist of the places, the instructors, the students, the duration of time, the learning content, the activities enhancing learning, the cultures of a group, the expected learning outcomes, and technologies. Also, [8] defined it as digital media; representatives of social communities and digital learning services are counted as the components of the learning ecosystem. The components of the learning ecosystem are biotic components such as the learners and the instructors, including the content creators, while abiotic components are equipment, devices or hardware, operating systems, and application programs or software, including network technology [6]. Similarly, it addressed that it comprises learners, instructors, learning equipment, learning areas that are not limited to time and place, and digital technologies [5]. For [9], the components of the learning ecosystem are both biotic components, such as a group of instructors and a group of learners, while abiotic components consist of teaching and learning materials, equipment, and devices used for teaching management, including instructions for managing to learn. In summary, the learning ecosystem consists of tools, learning equipment, learning areas, learning content, teaching and learning materials, teaching methods, and technologies such as hardware, software, a network system, an operating system, application programs, and biotic components such as a group of instructors, a group of learners and a group of learning supporters.

2.2. Machine Learning

Machine learning refers to studying patterns of algorithms and statistics that a computer system uses for specific tasks [10]. Also, it is one form of data analysis that uses models to analyze data automatically [11]. Moreover, it utilizes artificial intelligence while learning, and improvements can be made automatically with experiences [12]. It is also a subfield of artificial intelligence and computer science that aims to use data and algorithms to imitate human learning by improving its accuracy. In short, machine learning is a part of learning using machines as artificial intelligence for learning and improving, together with using learned experiences to determine how to automate data.

2.2.1. Types of machine learning

According to [10], there are two types of machine learning: supervised learning and unsupervised learning. Supervised learning refers to mapping input-output pairs to infer a function from a labeled training dataset. The input dataset is split into the training and the testing data. The output variable of the training data is predicted and classified. Every algorithm, such as Decision Tree (DT), Naïve Bayes (NB), and Support Vector Machine (SVM), learns some patterns from the training data and applies the data. For unsupervised learning, no correct answers and instructors are needed. Interesting structures in the data are discovered and presented by algorithms. They will learn some characteristics from the data. The data class is recognized from the previously learned characteristics when new data is fed. The most popular techniques for clustering and reducing features are Principal Component Analysis (PCA), a Neural Network (NN), and K-Nearest Neighbors (KNN).

a) Decision Tree

Decision tree learning is a popular and valuable method for inductive inference beyond data under supervision based on characteristics. It illustrates the steps of classifying information based on its category. It is used for significant data processing [13], but it is also a technique for giving a tree structure result consisting of nodes. Each node has a testing property to construct a decision. Attributes that relate to class the most is a root node [14] by finding the relevance of the attributes or information from the following formula [15]:

$$IG\ (parent,\ child) = entropy(parent) - [p(c1) \times entropy(c1) + p(c2) \times entropy(c2) + \ldots] \quad (1)$$

When entropy(c1) = -p(c1) log p(c1) and p(c1) is a probability of c1

b) Naïve Bayes

Naïve Bayes is a technique to calculate the probability by predicting prior events. It is a classification technique based on a theory of Naïve Bayes by assuming independence between the predictive models. Naïve Bayes classifiers show no relevance between existing specific features and the other existing features. The formula [16] is:

$$P(B|A) = P(A|B) \times P(B)\ P(A) \quad (2)$$

where;

P(B|A) is the probability of event B when event A occurs before

P(B|B) is the probability of event A when event B occurs before

P(A) is the probability of the occurrence of event A, and P(B) is the probability of the occurrence of event B.

c) Neural Network

A neural network is an artificial network referring to a biological neuron circuit. Modern use refers to artificial networks made from neurons or artificial nodes. It is a helpful model for calculation in computer science and other research studies. NN consists of neural units or neurons, so each neuron interconnects to other neurons. Although its system is not programmed, it can learn and train by itself. NN aims to operate like a human brain to solve problems [17].

2.3. Efficiency Evaluation of the Predictive Models

Accuracy, Recall, Precision, and F-measure were used to evaluate the efficiency of the models in the prediction of grade point average.

Accuracy used for measuring accuracy is regarded as a specific characteristic of accurate measurement. The closer the value is to the actual value, the more accurate the measurement [13][16] is.

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+FN+TN} \quad (3)$$

Recall refers to the ratio of accurate data found from all correct data.

$$\text{Recall} = \frac{TP}{TP+FN} \quad (4)$$

Precision is the ability to repeat the exact value of the measurement result, and it is the ratio of finding correct data from all retrieved data.

$$\text{Precision} = \frac{TP}{TP+FP} \quad (5)$$

The F-measure is an overall measurement of Recall and Precision.

$$\text{F-measure} = \frac{2\ x\ Precision\ \ x\ Recall}{Precision\ +Recall} \quad (6)$$

Where TP is the number of extracted correct data.
FP is the number of extracted incorrect data.
TN is the number of correct unextracted data.
FN is the number of incorrect unextracted data.

2.4. Synthesize Documents and Related Research

Synthesize documents and research relate to attributes used to predict an increase in undergraduate students' GPA levels. This is shown in Table 1.

Table 1. Factors of machine learning prediction to enhance the GPA of undergraduate students.

Factors	Related Work
Gender	[18], [19], [20]
Grades of courses	[21],[18], [22]
Courses	[21], [18], [23], [22]
GPA	[21], [18], [23], [22], [19], [20]

Table 1 is a synthesis of documents and research related to prediction for improving GPA levels. The factors used were Gender, Grades of courses, Courses, and GPA.

3. Methods

3.1. Learning Ecosystem

Conducting research on learning ecosystems to improve grades. Providing teaching and learning in an environment of the learning ecosystem in the fields of computer technology and the digital industry at the Faculty of Industrial Technology at Nakhon Si Thammarat Rajabhat University, as shown in Figure 1.

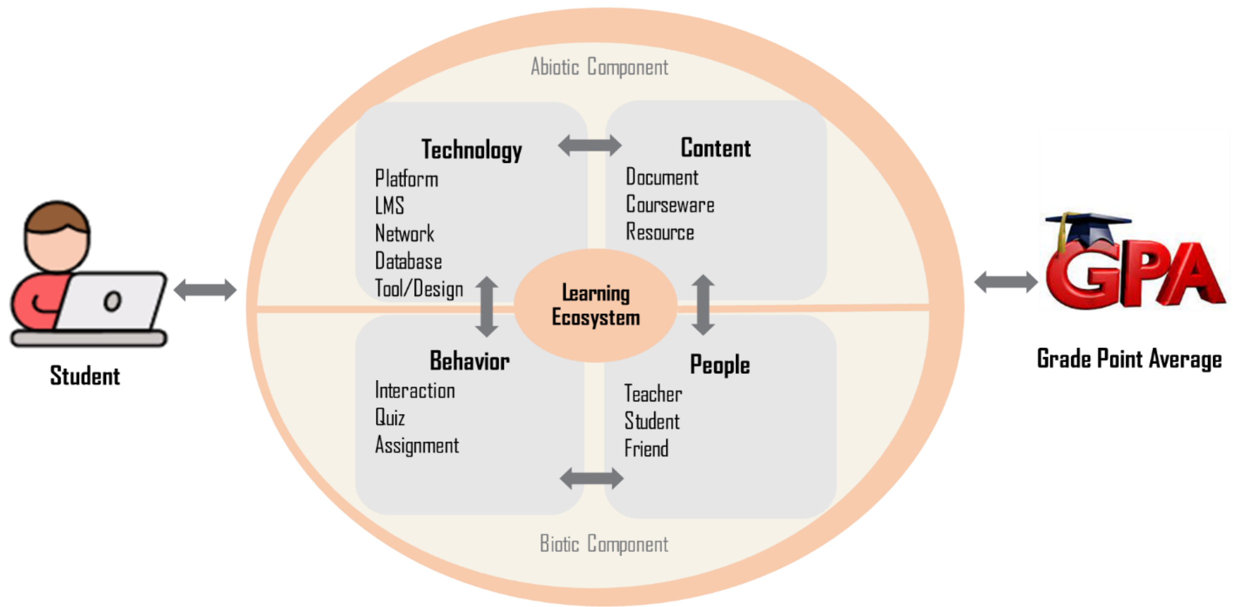

Figure 1. Learning Ecosystem, Faculty of Industrial Technology Nakhon Si Thammarat Rajabhat University

Figure 1 consists of two parts: Part 1 is an Abiotic Component, and Part 2 is a Biotic Component. Details are as follows.

Abiotic Components consist of *Technology* and *Content* described as follows:

Technologies consist of *Platforms* used in teaching and learning management or as a source of information research. *LMS (Learning Management System)* is a tool for organizing online teaching and learning systems via the internet. A *Cloud database* is used to store scores and exam results. The *Tools/Designs* are used in each course according to the details of a course.

Contents contain *Documents* in a course and files stored on the LMS system in documents for learners to facilitate their studies. *Courseware* in computer technology and digital industry courses. *Resources* used for teaching and learning such as Classrooms, Computer laboratories, Networking laboratories, Computer graphics, and Computer laboratories.

Biotic Components *consist* of *Behavior* and *People* described as follows:

Behaviors of learners and related persons. *Interaction* between the teachers and the learners. *Interaction* between learners, answering and helping learners in class. Assign quizzes to learners during the mid-semester and at the end of the semester. *Assignment* of tasks to learners during teaching.

People *involved* include teachers, students, and friends in the class.

3.2. Population and Sample

A total of 105 undergraduate students from the Computer Technology and Digital Industry Department, Faculty of Industrial Technology, Nakhon Si Thammarat Rajabhat University, formed the population of this study. The sample comprised 32 graduates who graduated from the Computer Technology and Digital Industry Department, Faculty of Industrial Technology, Nakhon Si Thammarat Rajabhat University in 2020.

3.3. Data Collection

The grade point average and grades were collected from 16 fundamental courses in Computer Technology during the academic years 2017 to 2020 of students admitted in the *first* semester of the academic year of 2017 who graduated in the second semester of the academic year of 2020. Sixteen were male, 16 were female, and data were collected from 42 courses, 124 credits, in Computer Technology and Digital Industry.

3.4. Data Set Selection

The data set used in the experiment was selected from 42 courses and 124 credits, and then tested with the weight of the courses that influenced the development of the GPA level. It appeared that only 16 courses in a specific category of the branch were submitted. This affects GPA, so the dataset used was Gender and the students' grades collected from the 16 fundamental courses: 5702207, 570206, 5701206, 5702205, 5703210, 5701208, 5702204, 5701204, 5703209, 5701207, 5701203, 5702203, 5702208, 5703208, 5701205, and 5701105, which were the factors affecting the grade point average of the students. Table 1 shows the data used to predict GPA for the analysis and the factors affecting the grade point average of the students.

Table 1. Factors of data for predicting GPA

Factors	Details
Gender	1= Male, 2= Female
Grades of 16 courses: 5702207, 5702206, 5701206, 5702205, 5703210, 5701208, 5702204, 5701204, 5703209, 5701207, 5701203, 5702203, 5702208, 5703208, 5701205, 5701105	4.0 = A, 3.5 = B+ 3.0 = B, 2.5 = C+ 2.0 = C, 1.5 = D+ 1.0 = D, 0.0 = E
Grade Point Average (GPA)	Poor = 0-1.90 Middle = 2.0-2.90 Good = 3.00-4.00

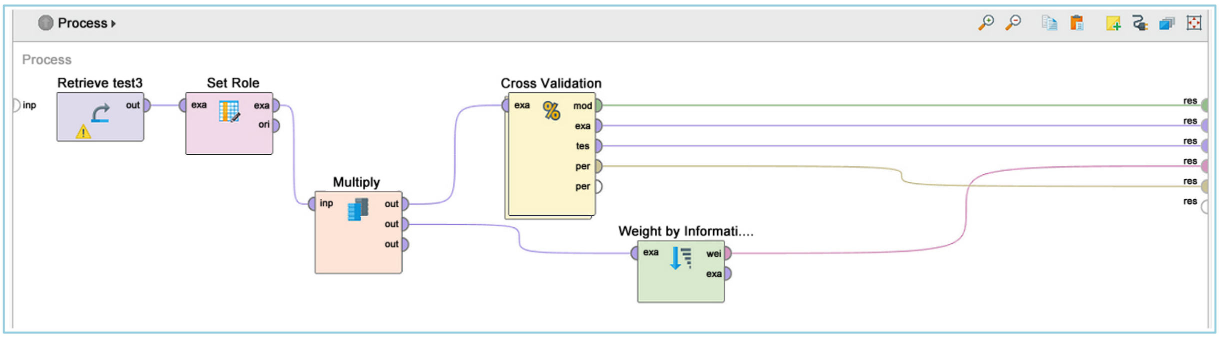

Figure 2. The DT model of The Machine Learning Ecosystem

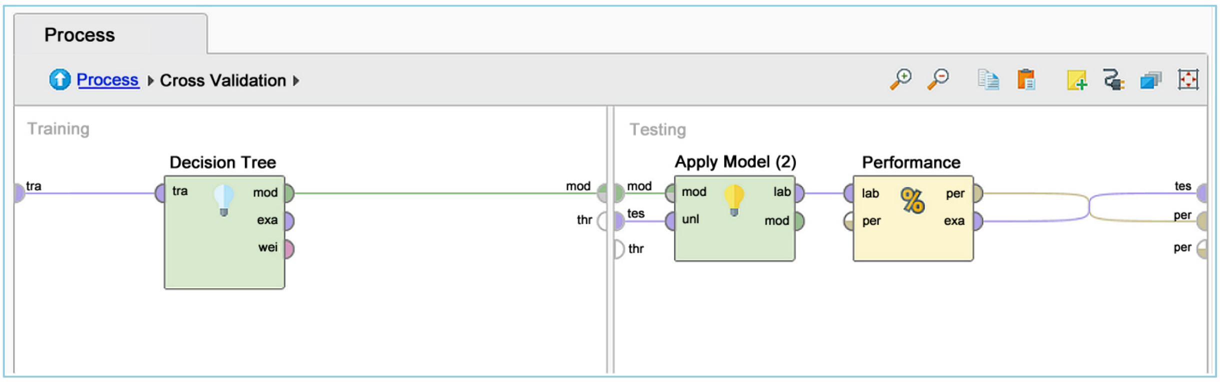

Figure 3. The DT model of The Machine Learning Ecosystem

3.5. Machine Learning Ecosystem Model

This study proposed a Machine Learning Ecosystem model using the Rapid Miner Studio program to predict the students' GPA to compare the efficiency of the three predictive models: DT, NB, and NN. This was done by dividing the data into two parts: 70% for the training models and 30% for testing the models. The evaluation uses a 10-fold cross-validation of the three learning ecosystem models to predict the GPA of undergraduate students in the Computer Technologies and Digital Industrial department as follows:

3.5.1. Decision Tree

The Machine Learning Ecosystem model using DT is shown in Figure 2 and Figure 3.

accuracy: 100.00% +/- 0.00% (micro average: 100.00%)

	true Good	true middle	class precision
pred. Good	21	0	100.00%
pred. middle	0	11	100.00%
class recall	100.00%	100.00%	

Figure 4. The efficiency of the DT model of The Machine Learning Ecosystem

As shown in Figure 4, the efficiency of the DT model of the Machine Learning Ecosystem for predicting the student's GPA was presented in the confusion matrix, precision, recall, and accuracy values.

3.5.2. Na ïve Bayes

The Machine Learning Ecosystem model using NB is shown in Figure 5 and Figure 6.

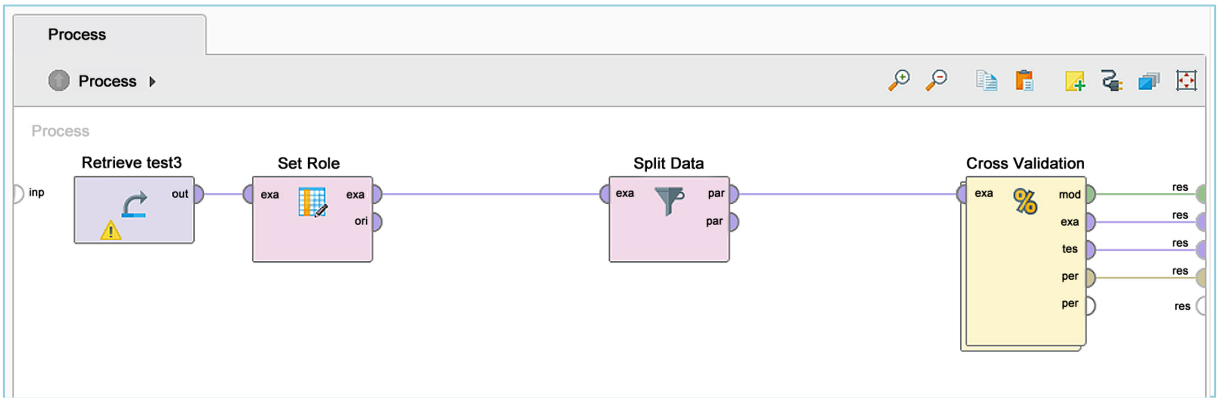

Figure 5. The NB model of The Machine Learning Ecosystem

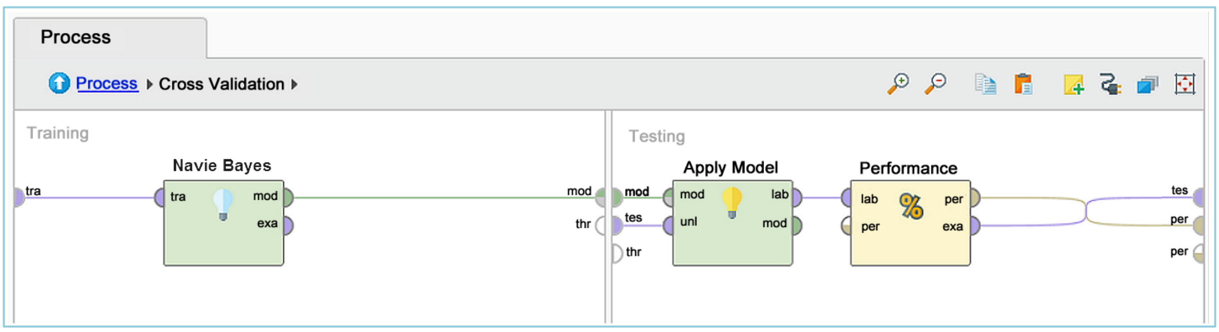

Figure 6. The NB model of The Machine Learning Ecosystem

accuracy: 81.67% +/- 25.40% (micro average: 78.26%)

	true Good	true middle	class precision
pred. Good	12	2	85.71%
pred. middle	3	6	66.67%
class recall	80.00%	75.00%	

Figure 7. The efficiency of the NB model of The Machine Learning Ecosystem

As displayed in Figure 7, the efficiency of the NB model of the Machine Learning Ecosystem for predicting the student's GPA was presented in the confusion matrix, precision, recall, and accuracy values.

3.5.3. Neural Network

The Machine Learning Ecosystem model using NN is shown in Figure 8 and Figure 9.

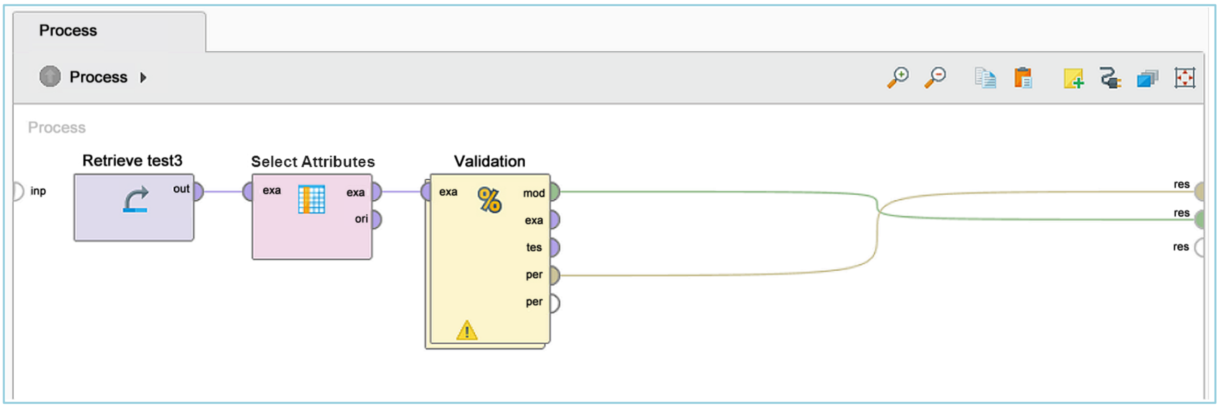

Figure 8. The NN model of The Machine Learning Ecosystem

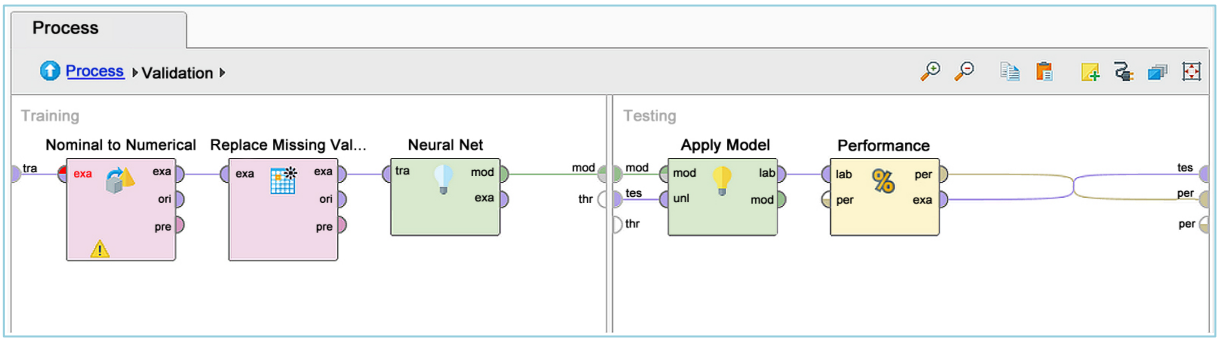

Figure 9. The NN model of The Machine Learning Ecosystem

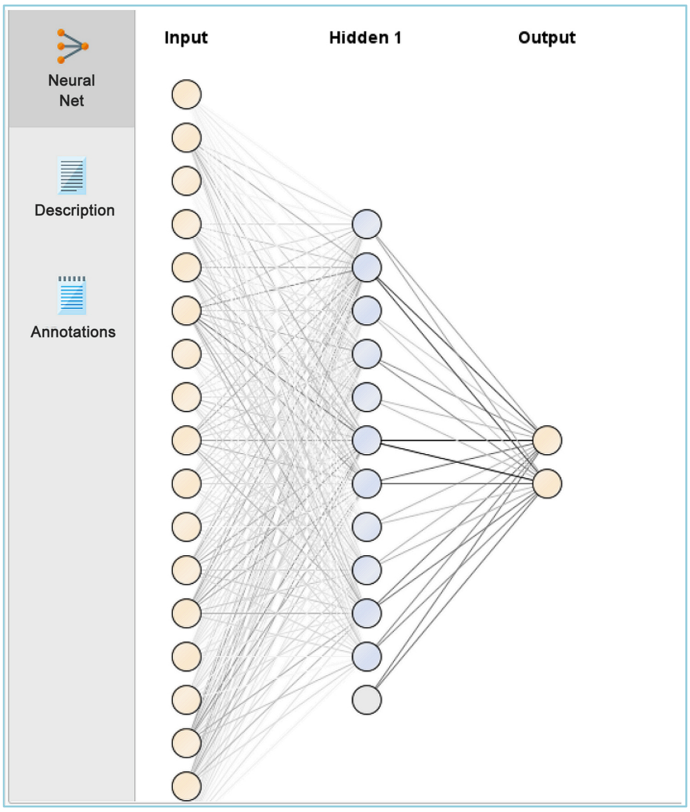

Figure 10. The NN model of The Machine Learning Ecosystem

accuracy: 85.83% +/- 19.27% (micro average: 84.38%)

	true Good	true middle	class precision
pred. Good	19	3	86.36%
pred. middle	2	8	80.00%
class recall	90.48%	72.73%	

Figure 11. The efficiency of the NN model of The Machine Learning Ecosystem

Figure 10 presents the NN model of the Machine Learning Ecosystem for *predicting* the students' GPA. One hidden node was found from 17 nodes of the input and two nodes of the output, namely, Middle GPA referring to a GPA of 2.00 - 2.90 and a Good GPA referring to a GPA of 3.00 - 4.00.

Figure 11 shows the efficiency of the NN model of the Machine Learning Ecosystem for predicting the students' GPA was presented in the confusion matrix showing the precision, recall, and accuracy values of the model.

4. Result

The Machine Learning Ecosystem model was built and tested using the DT, NB, and *NN* models. The results of the experiments are summarized below:

4.1. Efficiency of the Machine Learning Ecosystem Model

The modeling and testing results of the three learning ecosystem models: DT, NB, and *NN*, as well as accuracy, recall, and precision values, are shown in Table 2 below.

As shown in Table 2, the DT model has the highest accuracy (100.00%). NN achieved the second-highest accuracy (85.83%), while NB achieved the lowest accuracy (81.67%) of the three models.

Table 2. Accuracy values of the learning ecosystem models

Models for predicting GPA	Accuracy (%)
DT	100.00
NB	81.67
NN	85.83

Table 3. The efficiency of the Machine Learning Ecosystem model in the *Middle* group (2.00 - 2.90)

Model	Recall (%)	Precision (%)
DT	100.00	100.00
NB	75.00	66.67
NN	72.73	80.88

Table 3 shows the efficiency of the Machine Learning Ecosystem models for *predicting* the students' GPAs. For the *Middle* GPA (2.00 - 2.90), accuracy with DT, NB, and NN, was 100%, 75%, and 72.3%, respectively.

Furthermore, the DT model has the highest precision (100.00%) while the NN model has the second-highest precision (80.88%), and the NB model has the lowest precision (66.67%).

Table 4. The efficiency of the Machine Learning Ecosystem model in the *Good* group (3.00 - 4.00)

Model	Recall (%)	Precision (%)
DT	100.00	100.00
NB	80.00	85.71
NN	94.48	86.36

Table 4 shows the efficiency of the Machine Learning Ecosystem models in predicting the GPA of students in the *Good* group (3.00-4.00). The DT model has the highest recall (100%) and the *highest* precision (100%). The NN model has the second-highest recall (94.48%) and the second-highest precision (86.36%). The NB model has the lowest recall (80%) and the lowest precision (85.71%).

Table 5. The overall efficiency Machine Learning Ecosystem model

Models predicting GPAs	F-measure (%) GPA ranging from 3.00 to 4.00 (*Good*)	F-measure (%) GPA ranging from 2.00 to 2.90 (*Middle*)
DT	100.00	100.00
NB	84.79	70.59
NN	90.24	76.59

The F-measure of the Machine Learning Ecosystem models. For the *Good* Group (3.00-4.00), the DT model has the highest F-measure (100.00%), the NN model has the second highest F-measure (90.24%), while the NB model has the lowest F-measure (84.79%).

For the *Middle* Group (2.00-2.90), the DT model also achieved the highest F-*measure* (100.00%). The NN model has the second-highest F-measure (76.59%), while the NB model has the lowest F-measure (70.59%).

The experiments in each model summarize efficiency including Accuracy, Recall, Precision, and F-measure in two groups as shown in Table 6.

Table 6. Summary of the efficiency of the three models

Group	Efficiency	DT	NB	NN
	Accuracy (%)	100.00	81.67	85.83
2.00 - 2.90 (*Middle*)	Recall (%)	100.00	75.00	72.73
	Precision (%)	100.00	66.67	80.88
	F-measure (%)	100.00	70.59	76.59
3.00 - 4.00 (*Good*)	Recall (%)	100.00	80.00	94.48
	Precision (%)	100.00	85.71	86.36
	F-measure (%)	100.00	84.79	90.24

4.2. Information Gain Value in Qualifying Features

From creating and testing the models of a Machine *Learning* Ecosystem that affect the development of learning outcomes, the information gained was obtained from a selection of the characteristics of predictive factors, as shown in Table 7.

Table 7. Information Gain value in feature selection

No.	Factors	Weight
1	5702207	0.521
2	5702206	0.435
3	5703208	0.435
4	5702205	0.433
5	5703210	0.345
6	5701208	0.331
7	5701203	0.278
8	5701204	0.243
9	5703209	0.235
10	5701207	0.218
11	5702204	0.218
12	5702203	0.218
13	5702208	0.208
14	5701206	0.158
15	5701205	0.127
16	5701105	0.061

Table 7 shows the results of the calculation for the selection of qualifications using the Information Gain technique. It was found that 16-course attributes had an Information Gain value of the courses that were important to the resulting level. Information Gain values in Table 7 are obtained from the results of the experiment using the Information Gain technique. In Table 8, the researcher has classified characteristics that are important to the level of academic performance in 16 courses.

Table 8. Courses that affect the development of GPA

ID course	Name course
5702207	Software engineering
5702206	Animation technology
5703208	Advanced program development in industrial applications
5702205	Web programming and applications
5703210	Mobile application design and development
5701208	Database system
5701203	Multimedia technology
5701204	computer graphics
5703209	A new paradigm in computer technology and the digital industry
5701207	Data structures and algorithms

Table 8 shows courses in a specific subject category that affect the development of GPA. These are 5702207 Software engineering, 5702206 Animation technology, 5703208 Advanced program development in industrial applications, 5702205 Web programming and applications, 5703210 Mobile application design and development, 5701208 Database system, 5701203 Multimedia technology, 5701204 Computer graphics, 5703209 A new paradigm in computer technology and digital industry, and 5701207 Data structures and algorithms.

5. Conclusion

This study aimed to 1) develop models of a Machine Learning Ecosystem to enhance grade point averages, and 2) predict grade point averages by modeling machine learning ecosystem techniques, namely, Decision Trees (DT), Naïve Bayes (NB), and a Neural Network (NN). The researcher divided the grades into three groups: Group 1 had grades between 0.00 – 0.19 *(Poor)*, Group 2 had grades between 2.0-2.90 *(Middle)*, and Group 3 had grades between 3.00-4.00 *(Good)*. Three algorithms were used to create and test the Machine Learning Ecosystem model, DT, NB, and NN, using the Rapid Miner program, with a 10-fold cross-validation assessment.

5.1. Compare the Performance of the Tree-Based Algorithm

In the experiment it was found that learners could be classified into two groups, namely the *Middle* group and the *Good* group, meaning that the learners had a grade of 2.00 or higher and were able to classify the efficiency of the Machine Learning Ecosystem. The DT model was the most effective (Accuracy = 100.00%). The predictive accuracy of the model, when classified by a group of learners, found that both groups of the DT model had the highest accuracy (Precision = 100%) and in each group. The DT model had the highest F-measure (100%).

5.2. Machine Learning Ecosystem to Improve GPA

A Machine Learning Ecosystem can find courses that affect GPA levels. In this study, the researcher began by experimenting with 40 courses, 10 general education courses, and 30 specialized courses. The experiment was conducted using the GPA of all courses. Courses that did not affect the GPA level were excluded, leaving 16 subjects in a specific category of the curriculum. Therefore, this research found that the Machine Learning Ecosystem Model can solve problems related to the importance of choosing a course category of an educational institution and should focus on facilitating teaching management in a specific course category. Providing equipment and tools to support the Learning Ecosystem, both Abiotic Component and Biotic Component in specific courses, rather than courses in other categories, directly develops students' GPA levels.

5.3. Utilizing the Machine Learning Ecosystem

The researcher provided training on how to use the Machine Learning Ecosystem to lecturers in the Computer Innovation and Digital Industry Department. This research example is a guide to increasing students' GPA levels, and from training in the use of the Machine Learning Ecosystem, it was discovered that the facilities needed to increase students' GPA levels must be provided in courses such as Microprocessor and Microcontroller requires Internet of Things training kit (IoT kit), which is an Abiotic Component of the Learning Ecosystem. One more instructor should be added to teach courses on data structures and algorithms, which are Biotic components of the Learning Ecosystem. It is expected that the student's GPA level will increase in the next generation of graduates.

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