Genetic Assessment Agent for High-School Student and Machine Co-Learning Model Construction on Computational Intelligence Experience

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***Abstract*—This paper presents a genetic assessment agent and a student and machine co-learning model for high-school students' computational intelligence (CI) experience. We invited the IEEE CIS High School Outreach (HSO) subcommittee members of the years 2021-2022 to provide lectures at CIS activities and conferences and constructed a basic CI conceptual knowledge structure for high-school student learning. From 2021 to 2022 in Taiwan, we collected high-school students' learning data, including labels, attitudes, environment, and effort, from the CI&AI-FML platform using robots and learning tools, then processed the data using natural language processing (NLP) techniques to efficiently evaluate high-school students' learning state. We then applied three evolutionary computation techniques: genetic algorithm (GA), particle swarm optimization (PSO), and genetic algorithm neural network (GANN) in the proposed genetic assessment agent for the co-learning model, with learning performance regression analysis. In this paper, a CI&AI-FML human and machine co-learning Metaverse model is presented as a solution, which provides hands-on learning and experience while also supporting student-centered online learning during the COVID-19 pandemic. Students participated in the course during the 2022 Spring semester to learn basic CI concepts and experience CI applications through interaction with machines using the developed CI&AI-FML learning tools. The experimental results indicate that the genetic assessment agent with the GANN method has better performance in the student and machine co-learning model as compared to the other two methods, and it is effective for student and machine co-learning model construction.**

Keywords—Genetic Assessment Agent, CI Learning Concept, High-School Student CI Experience Model, Natural Language Processing, Machine Learning

I. INTRODUCTION

In recent years, the COVID-19 pandemic has forced schools to adopt the online teaching mode to conduct classes, share resources, and do homework [1]. Additionally, the proliferation of the Internet and the emergence of social media technologies have led to the evolution of digital learning [2]. Lee et al. [3] proposed an Artificial Intelligence (AI)-Fuzzy Markup Language (FML) Metaverse for elementary and high-school students to learn English and FML. The AI-FML Metaverse provides a more interactive and student-centered human and smart machine co-learning environment to help more students learn about computational intelligence (CI) and CI&AI-FML.

From 2017 to 2022, Lee et al. [4], [5] held related events of CI&AI-FML learning in Taiwan or at conferences. In addition, they also cooperated with some schools in Taiwan to open related CI&AI-FML learning courses. The total number of participants has reached over 8,300 in the past five years. The main objective is to make the participants learn more about computational intelligence (CI) with the machine learning method and how it shapes our world. In the AI-FML Metaverse, students learn CI, including fuzzy logic (FL), neural network (NN), and evolutionary computation (EC), to further understand the basic concepts of machine learning. They learn how to use CI&AI-FML tools for image recognition and fuzzy inference and apply them to make travel recommendations. The participants also participate in a fun competition that tests their skills learned during the event.

The IEEE Computational Intelligence Society (CIS) values and promotes education by supporting summer schools and high school educational programs worldwide. EC is part of CI and evolutionary algorithms are bio-inspired optimization algorithms used to efficiently solve hard problems [6]. According to Xue et al. [7], a variety of EC algorithms have recently been used to address feature selection tasks. Gad [8] developed a python library, PyGAD, to enable learners to build genetic algorithms to optimize trained models using machine learning algorithms. Lee et al. [9] used FML combined with particle swarm optimization (PSO) to evaluate student learning performance in educational applications and genetic algorithms (GA) to assess healthy diet [10].

Under an interactive AI-FML Metaverse, students learn CI&AI-FML and label the key CI learning concepts that they learned in class. This paper uses natural language processing (NLP) tools, including Chinese Knowledge Information Processing (CKIP) and fastText [11], to analyze data collected and evaluate the learning state of high-school students in gaining knowledge of CI applications. A genetic assessment agent is proposed to evaluate the student's progress in CI&AI-FML based on machine intelligence (MI) and observations from students and teachers, as well as the conditions of the learning environment. A knowledge base (KB) and rule base (RB) for high-school student learning are constructed to train the model and evaluate the performance of regression using GA-based FML (GFML), PSO-based FML (PFML), and GANN methods. The results show that the genetic assessment agent with the

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GANN method performs better than the GFML and PFML methods.

The paper proposes a novel approach to teaching pre-university students the concepts of CI which are designed to promote interactive and hands-on learning and playing. A CI&AI-FML human and machine co-learning Metaverse model is presented as a solution, which provides hands-on learning and experience while also supporting student-centered online learning during the COVID-19 pandemic. The proposed approach includes a genetic assessment agent that utilizes NLP and machine learning techniques, such as genetic algorithm, particle swarm optimization, and genetic algorithm neural network, to analyze students' learning state.

The remainder of this paper is structured as follows: Section II briefly introduces the high-school student and machine co-learning model for the CI experience. Section III describes the knowledge graph of basic CI concept learning for the CI experience. Then, in Section IV, we introduce the proposed genetic assessment agent for high-school students and machine co-learning model construction. Finally, experimental results are shown in Section V, and the conclusions are presented in Section VI.

II. High-School Student and Machine Co-Learning Model for Computational Intelligence Experience

A. *Human and Machine Co-Learning Model*

Fig. 1 shows the structure of the CI&AI-FML human and machine co-learning model composed of an AI-FML Metaverse, an NLP preprocessing agent, and a genetic assessment agent. This model is inspired by the thoughts and spirits of human intelligence (HI). The student learning content is based on the core concepts of CI and its conceptual knowledge structure is also built. This paper promotes and validates this model through the Students' Club and multi-elective courses during the Spring Semester of 2022 at four high schools in Taiwan.

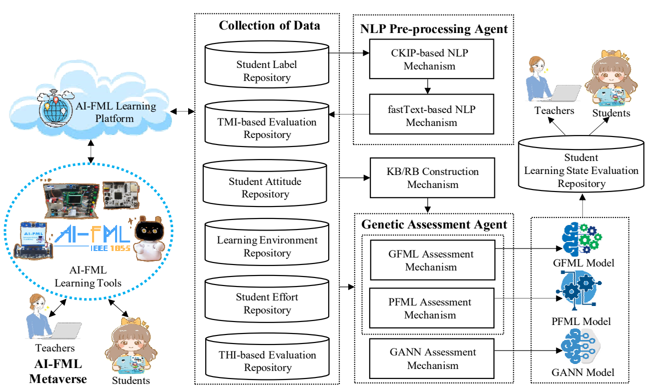


Fig. 1. Structure of CI&AI-FML human and machine co-learning model.

We adopt five stages to collect the involved high-school students' learning data and analyze their learning status, including (1) collecting related data in the AI-FML Metaverse, (2) implementing data preprocessing and learning state analysis through human intelligence (HI) and machine intelligence (MI), (3) constructing a related KB and RB based on the data collection to infer the high-school students' learning state, (4) optimizing the high-school learning CI&AI-FML co-learning model with genetic assessment agent through the use of GFML, PFML, and GANN, and (5) analyzing the students' learning state and then providing feedback to the involved teachers and students.

B. *CI Conceptual Knowledge Structure*

Fig. 2 shows the conceptual knowledge structure of the CI&AI-FML human and machine co-learning model, including CI&AI-FML learning tools, involved schools in Taiwan, equipment in the learning field, and virtual/physical classroom in the learning field. This paper focuses on the student's learning state analysis of four courses opened at three specific high schools, including Rende Junior High School (RDJH), Guiren Junior High School (GRJH), and Tsoying Senior High School (TYHS). Each classroom is equipped with different tools that are essential for students and teachers such as computers, touch screens, and tablets, in addition to CI&AI-FML learning tools. Take RDJH for an example. The classroom of RDJH is equipped with the AI-FML Robot, laptop, AI-FML Learning Tool, and a TV screen. During the course, the students interact with the CI&AI-FML learning tools to experience CI learning via tools and equipment in the learning environment and learn CI conceptual knowledge through the virtual or physical classroom.

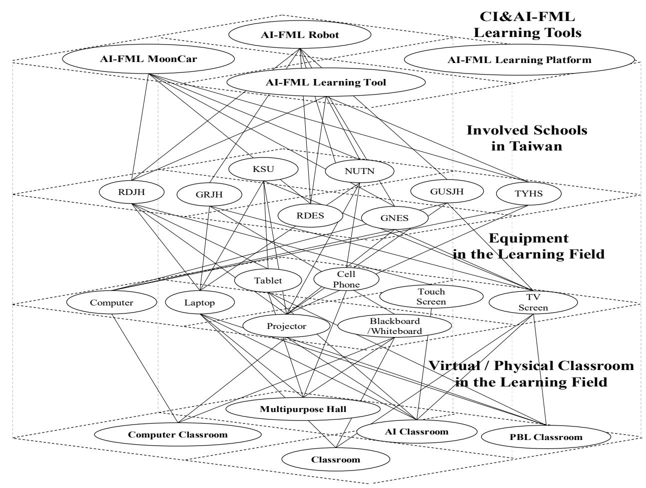


Fig. 2. Conceptual knowledge structure of the CI&AI-FML human and machine co-learning model.

III. Knowledge Graph for Basic Computational Intelligence Concept Learning and Experience

A. *Basic CI Conceptual Knowledge for High-School Students Learning and Experience Evolution*

Fig. 3 shows an example of the basic conceptual CI knowledge model, including *Junior Course Model 1 with 14 hours* (JCM 1), *Junior Course Model 2 with 23 hours* (JCM 2), *Senior Course Model 3 with 14 hours* (SCM 3), and *Senior Course Model 4 with 27 hours* (SCM 4) for human learning evolution from junior to the senior high-school student experience and learning. Fig. 4 and Fig. 5 show the detailed basic CI conceptual knowledge provided in JCM 2 (AI-FML Club, RDJH, Taiwan) and SCM 4 (Robotics Project, TYHS, Taiwan), respectively, which are described as follows:

- In the CI&AI-FML Metaverse, young high-school students gained knowledge about basic CI concepts through the identified experience-based learning, concept-based learning, operation-based learning, practice-based learning, expression-based learning, and application-based learning. It indicates that the human learning evolution from junior to senior high-school students involves changes in learning hours, from 14 hours to 27 hours, and an increase in the quantity of learning content.

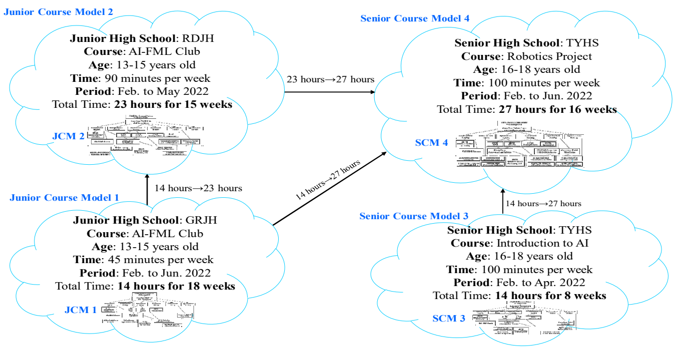


Fig. 3. Example of basic Conceptual CI knowledge model for human learning evolution from junior to senior high-school student experience and learning.

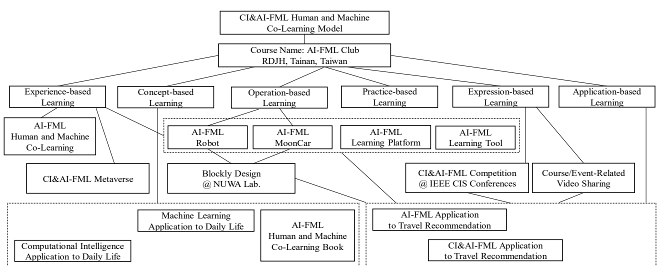


Fig. 4. Example of basic conceptual knowledge structure JCM 2 for junior high-school students' CI experience.

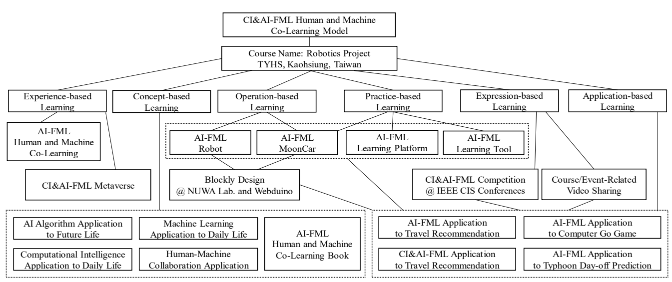


Fig. 5. Example of basic conceptual knowledge structure SCM 4 for senior high-school students' CI experience.

- SCM 4 has the most comprehensive learning content and the longest total teaching hours of 27 hours over 16 weeks among the four courses. For example, students experience and operate AI-FML Robot, MoonCar, Learning Platform, and Learning Tool, as well as apply what they learned to four applications (AI-FML travel recommendation, CI&AI-FML travel recommendation, AI-FML computer Go game, and AI-FML typhoon day-off prediction).
- JCM 1 has the least learning content due to its total learning hours of 15 hours. Students in SCM 4 may acquire the most in-depth CI conceptual knowledge, while JCM 1 may provide the least. It may be beneficial to design more concept-based and operation-based learning for senior high-school students than for junior high-school students.
- After learning, the RDJH students demonstrated their learning performance to one of the 2022 IEEE HSO Subcommittee members (https://youtu.be/rcUocpSfAVs). They successfully competed in Category B of the IEEE WCCI 2022 competition, achieving first place (https://youtu.be/DVKU2fFH3vs).

B. *Knowledge Graph for Basic CI Experience*

Fig. 6 shows an example of a basic CI knowledge graph for high school student learning and experience described as follows: (1) The gray-colored node represents that the students of JCM 1, JCM 2, SCM 3, and SCM 4 were not taught during the 2022 Spring Semester. (2) We have designed more hours of practicing CI for senior high school students as compared to junior high school students. (3) CI encompasses three main concepts: NN (GANN), EC (GANN, GA, and PSO), and FL (KB and RB). (4) The CI and AI-FML application for *Travel Recommendation* is one type of CI application and it is incorporated into the CI experience and practice through the utilization of image and voice recognition from Google Teachable Machine and NUWA Lab, as well as the construction of a KB and RB from the AI-FML platform or AI-FML Lab. (5) The CI and AI-FML application for *Travel Recommendation* utilizes four types of data, including voice, image, text, and numerical. (6) NUWA Lab, AI-FML platform, Google Teachable Machine, and AI-FML Lab are examples of software platforms in the CI&AI-FML Metaverse.

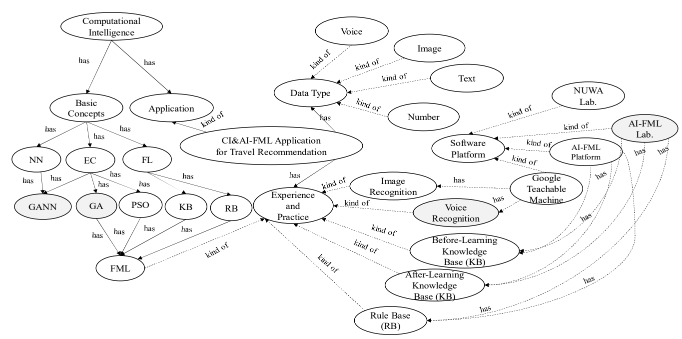


Fig. 6. Example of a basic CI knowledge graph for high school student learning and experience.

IV. GENETIC ASSESSMENT AGENT FOR HIGH SCHOOL STUDENT AND MACHINE CO-LEARNING MODEL CONSTRUCTION

A. *Genetic Assessment Agent Structure*

Fig. 7 illustrates the structure of the genetic assessment agent for high-school students and machine co-learning model construction, comprising GFML, PFML, and GANN. Four features are selected from the data collection, including a *Temperature of Machine Intelligence* (*TMI*)-based evaluation repository, a *student attitude* repository, a *learning environment* repository, and a *student effort* repository. These are described as follows: 1) The *TMI-based evaluation* repository stores the students' learning state provided by the NLP preprocessing agent. We analyze the data collected through both quantitative (CKIP-based NLP mechanism) and qualitative (fastText-based NLP mechanism) methods [3] to evaluate the participant's learning state. Additionally, this paper uses the concept of a learning thermometer to measure students' level of engagement, interest, and motivation in the learning process, which is reflected in their learning temperature where a higher temperature indicates a better learning state. 2) The repository for *student attitude* stores feedback from students regarding what they learned, how they feel about co-learning with machines, and whether they would be willing to participate in the course again in the future. 3) The repository for the *learning environment* stores feedback from teachers regarding the working quality of the provided equipment and the stability of the internet during the course. 4) The repository for *student effort* stores information about the level of effort exerted by each student, including how well they cooperated with their peers, utilized the provided tools, and engaged in the course, as observed by teachers. 5) The target data is the *Temperature of Human Intelligence* (*THI*)*-based evaluation*, which represents the *students' learning temperature* as evaluated by their teachers. Finally, more than one teacher, whether in-person or virtually, is involved in the CI&AI-FML human and machine co-learning Metaverse to assist in teaching the participants. Therefore, the level of *student effort* and *THI-based evaluation* is measured by multiple teachers to reduce subjective measurement.

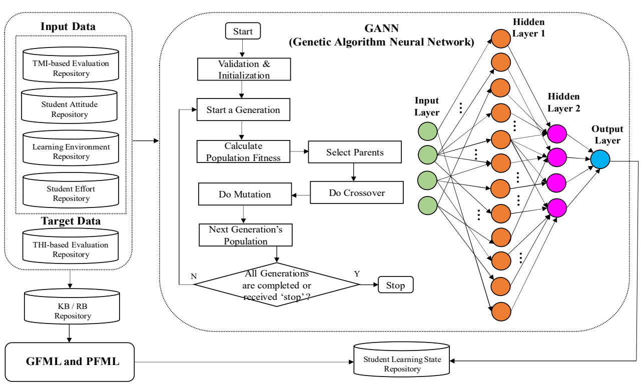


Fig. 7. Genetic assessment agent for student and machine co-learning model construction.

TABLE I. NAMES OF FUZZY VARIABLES AND LINGUISTIC TERMS.

Fuzzy Variable Name		Linguistic Term Name
Input	*TMI*	Reinforced/Passable/Good/Excellent
	SA	VeryPassive/Passive/Common/Active/VeryActive
	LE	Reinforced/Common/Excellent
	SE	Low/LowMedium/Medium/MediumHihg/High
Output	*SLS*	Reinforced/Passable/Good/Excellent

With the four features and target data, the KB and RB are constructed to make fuzzy inferences to optimize the GFML and PFML models with four input fuzzy variables *TMI*, *student attitude* (*SA*), *learning environment* (*LE*), *student effort* (*SE*) and one output fuzzy variable (*student learning state*, *SLS*). Table I shows the names of fuzzy variables and linguistic terms. These variables and terms cause the system to have $4 \times 5 \times 3 \times 5 = 300$ fuzzy rules, one for each combination of the input fuzzy variables. The GANN structure is composed of an input layer, two hidden layers, and an output layer. The input layer sends the four features to the subsequent layers. The adopted activation function of the two hidden layers is the ReLU function. In this paper, we used a shallow neural network comprising four layers with the following configuration: 4 input nodes, 12 nodes in the first hidden layer, 4 nodes in the second hidden layer, and a single output neuron. We use the genetic algorithm to train the neural network to optimize the student and machine co-learning model for high school students' CI experience using EC techniques. Depending on the performance of trained networks, the feature set will converge to a discriminative feature subset of the training data.

B. Genetic Assessment Agent Training Model

This subsection describes how to train the model for the dataset of SCM 4 using the proposed genetic assessment agent. Table II shows the genetic assessment agent training model algorithm. Fig. 8(a)-(f) shows fuzzy sets of the fuzzy variables *TMI*, *SA*, *LE*, *SE*, and *SLS*, respectively, of students' learning states in SCM 4.

TABLE II. GENETIC ASSESSMENT AGENT TRAINING MODEL ALGORITHM.

Input:
(1) *TraFeature* and *TraLabel*: Features and labels of the training dataset of SCM 4 after the NLP preprocessing agent
/*where features include *TMI*, *SA*, *LE*, *SE*, and the label is *THI**/
(2) *TstFeature* and *TstLabel*: Features and labels of the testing dataset of JCM1, JCM2, and SCM 3 after the NLP preprocessing agent.

Output:
(1) BLM: Before-learning model by IEEE 1855 Standard
(2) GFMLM: After-learning GFML model by IEEE 1855 Standard
(3) PFMLM: After-learning PFML model by IEEE 1855 Standard
(4) GANNM: After-learning GANN Model
(5) Fitness value after prediction based on the trained GFML, PFML, and GANN models

Method:
Step 1: Normalize the *TraFeature* and *TraLabel* to [0, 1]
Step 1.2: Calculate the minimum, maximum, and average for *TMI*, *SA*, *LE*, *SE*, and *THI* for SCM 4, respectively by considering the standard deviation for three groups
Step 1.2.1: $STD_1 \leftarrow$ standard deviation for data whose values are between minimum and average
Step 1.2.2: $STD_2 \leftarrow$ standard deviation for data whose values are between average and maximum
Step 1.2.3: $STD_3 \leftarrow$standard deviation for all data
Step 1.2.4: Construct the KB of the fuzzy variables *TMI*, *SA*, *LE*, *SE*, and *SLS* to acquire BLM.
Step 2: Set the loss function (*fitness_func*)
Step 3: Set the related parameters for GFML
Step 3.1: num_generations←2000, corssover_probability←0.9
Step 3.2: mutation_probability←0.1, num_solution←20
Step 3.3: parent_selection_type←roulette wheel selection
Step 3.4: crossover_type←single_point, mutation_type←random
Step 4: Input BLM, train GFML Model for the dataset of SCM 4 by the proposed method in [10], and save GFML Model
Step 5: Set the related parameters for PFML
Step 5.1: num_generations←2000, num_particle←20, Dimension←5
Step 6: Train PFML Model for the dataset of SCM 4 by the proposed method in [9], and save PFML Model.
Step 7: Set the related parameters for GANN
Step 7.1: num_solution←20, num_neurons_input←4
Step 7.2: num_neurons_hidden_layers←[12, 4] /*set 12 and 4 nodes to the hidden layers 1 and 2, respectively*/
Step 7.3: num_neurons_output←1, hidden_activations←[relu,relu] /*set the activation function of two hidden layers to the ReLu function.*/
Step 7.4: output_activation←'None'

Step 8: Set the related parameters for GA

Step 8.1: num_generations←2000, corssover_probability←0.9

Step 8.2: mutation_probability←0.1, num_solution←20

Step 8.3: parent_selection_type←roulette wheel selection

Step 8.4: crossover_type←single_point, mutation_type←random

Step 9: Optimize the GANN model using the genetic algorithm until the termination and save the GANN model

Step 10: Use the trained GFML, PFML, and GANN models to predict the *TraFeature* and *TstFeature*

Step 12: Save the results of the prediction

STEP 13: END

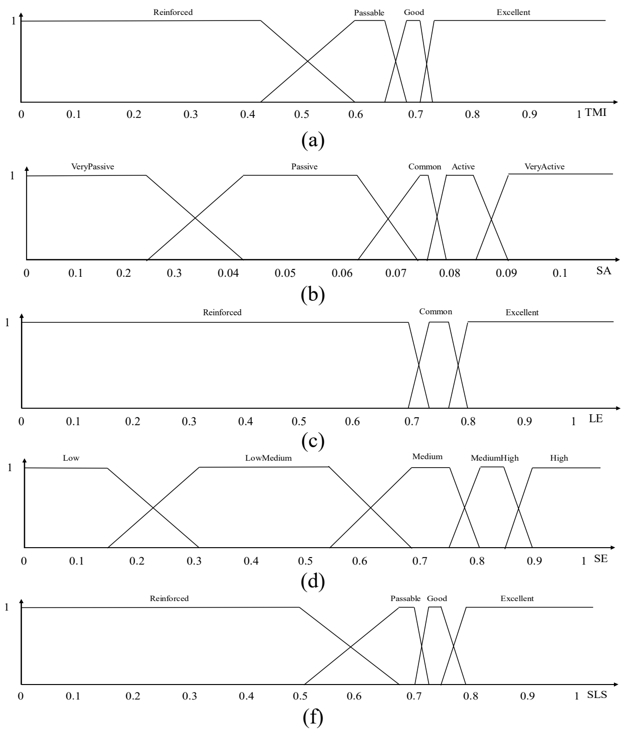


Fig. 8. Fuzzy sets of the fuzzy variables (a) *TMI*, (b) *SA*, (c) *LE*, (d) *SE*, and (f) *SLS* of students' learning state in SCM 4.

V. Experimental Results

A. Involved Students Profile

This section shows the experimental results of the genetic assessment agent for high school students' CI learning and experience across four learning fields, during the Spring Semester of 2022. Table III shows the profiles of the participating students in four courses (JCM 1, JCM 2, SCM 3, and SCM 4). As shown in Fig. 9, the students in SCM 4 had the highest data collection and the highest *average number of data collected* (*ANDC*) calculated by Eq. (1). JCM 2 has more data collected than JCM 1 but the *ANDC* is lower than JCM 1.

TABLE III. Involved Students' Profiles.

No.	Learning Field	Student No.	Group No.	Age	Time per week	Total Weeks
JCM 1	GRJH	15	5	13-15	45 mins	18
JCM 2	RDJH	15	4		90 mins	15
SCM 3	TYHS	20	4	16-18	100 mins	8
SCM 4		29	5			16

$$ANDC = \frac{\text{Number of Data Collected}}{\text{Total Weeks}\times\text{Time per Week}\times\text{Student No.}} \quad (1)$$

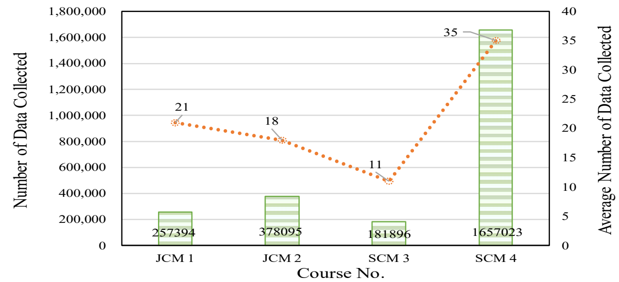


Fig. 9. The number of the data set and the *ANDC*.

B. JCM1 vs. JCM2 Comparison

This subsection compares the performance of students in JCM 1 and JCM 2. The differences between JCM 1 and JCM 2 include 1) *the period of each episode*: JCM 1 is 45 minutes while JCM 2 is 100 minutes; 2) *the gap between urban and rural areas*: the learning field of JCM 1 (GRJH) is located in a rural area while JCM 2 (RDJH) is much closer to the urban; 3) *the environment in the learning field*: students in JCM 1 should prepare their notebooks to take the course, however, sometimes students forget to bring them, which affects their learning performance.

Fig. 10(a)-(b) shows the average TMI and THI for each student and the entire class in JCM 1 and JCM 2, respectively. These figures indicate that the variance in student learning in JCM 1 is higher than in JCM 2. Group 5 (G5) of JCM 1 has the best performance, possibly because they have one year of experience in CI learning. Additionally, the overall average THI in JCM 2 is higher than in JCM 1, but the TMI is the opposite. This is likely because the TMI only considers students in the same learning field, while the THI uses the same criteria to evaluate all students' performance.

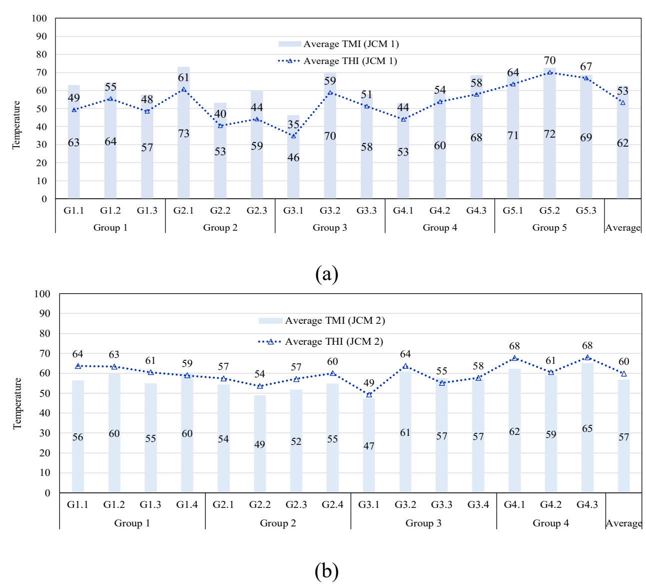


Fig. 10. Average TMI and THI for each student in (a) JCM 1 and (b) JCM 2.

C. SCM3 vs. SCM4 Comparison

Fig. 11 shows the curves of data collection for SCM 3 and SCM 4 during the Spring Semester of 2022. It can be observed that SCM 4 had a higher data collection than SCM 3. This is likely due to several factors. 1) *The number of course weeks*: SCM 3 is 8 weeks while SCM 4 is 16 weeks. 2) *The major of the students*: Science track for SCM 3 and social sciences track for SCM 4. Generally speaking, students in the social sciences track tend to have a stronger ability to articulate and document important concepts, as well as share their experiences in their electronic notebooks. 3) *The pressure of college entrance exams*: Senior three for SCM 3 while senior two for SCM 4. 4) *Learning Attitude*: Few students in SCM 3 were observed to be sleepy in class, while most students in SCM 4 were observed to be actively engaged and studying hard in class (5) *Absenteeism in class*: The rate of SCM 3 is 22/160 = 0.064 while SCM 4 is 30 / 464 = 0.137.

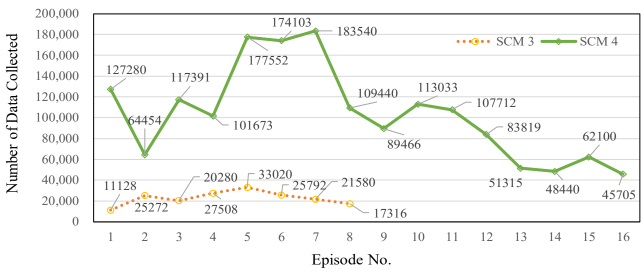


Fig. 11. The number of data collected for SCM 3 and SCM 4 during the 2022 Spring Semester.

Additionally, due to the COVID-19 situation in Taiwan, the teaching mode was changed from in-person to virtual starting from Episode No. 9 of SCM 4. This change was observed to result in a decrease in the amount of data collected. This suggests that in-person teaching may be more effective for high-school students learning CI. However, it should be noted that SCM 3 did not experience the shift to virtual teaching due to COVID-19, as all eight episodes of the course were conducted in person. Fig. 12 shows the average TMI for both SCM 3 and SCM 4. It can be seen that the students in SCM 4 have a higher performance in class as compared to SCM 3. However, the students in SCM 4 learned the contents shown in Fig. 5, while SCM 3 only learned some of the contents in Fig. 5 owing to the constraints of the course period. As a result, students in SCM 3 and SCM 4 may learn different topics in the same number of episodes.

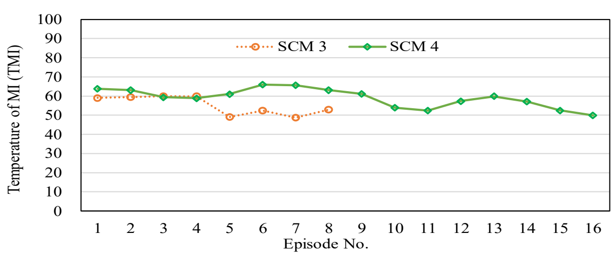


Fig. 12. Average TMI for SCM 3 and SCM 4.

D. Verification and Practice

This subsection presents the performance of students who participated in four courses after learning in the AI-FML Metaverse. Fig. 13 shows the AI-FML Metaverse framework for student learning described as follows: The students constructed a KB and RB for an FML-based inference system using machine learning tools for real-world travel recommendations. Additionally, the system can connect to AI-FML devices for simulating: 1) human brain and CI to control the speed of the AI-FML MoonCar, 2) human vision and intelligent recognition to send image recognition results to the AI-FML Robot, and 3) human voice recognition, human speech, and human activities to receive messages from the AI-FML MoonCar and speak the recognized results by the AI-FML Robot.

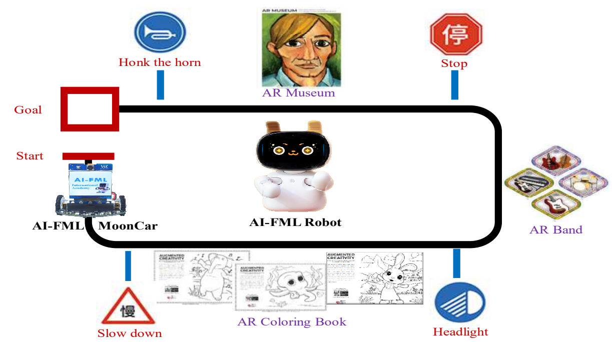
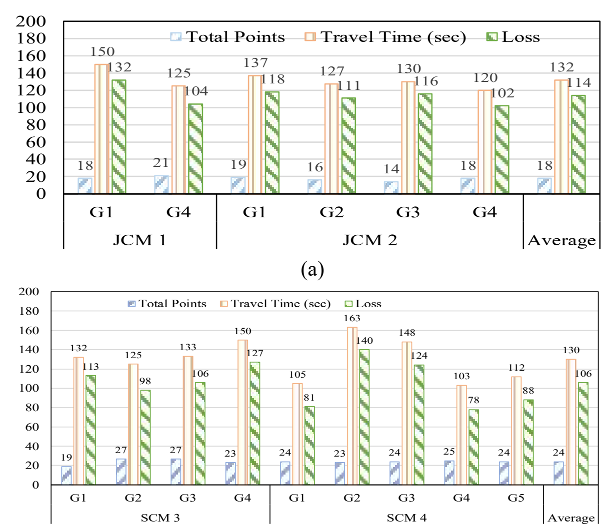


Fig. 13. AI-FML Metaverse framework for student learning.

TABLE IV. INFORMATION ABOUT THE INVOLVED STUDENTS AND RULES.

Course No.	Participation Group No.	Practice Date	Demonstration Link
JCM 1	G1 and G4	Mar. 23	N/A
JCM 2	G1 to G4	Mar. 18	https://youtu.be/Is_QmR6HGSA
SCM 3	G1 to G4	Mar. 21	N/A
SCM 4	G1 to G5	Mar. 21	https://youtu.be/xsrkrswhV4E
Rules			
• The objective function is the minimization of travel time while maximizing total points. The final loss value is calculated as the difference between travel time and total points, with the team with the lowest final loss being declared the winner. • The AI-FML learning platform controls the traveling speed of the AI-FML MoonCar using CI technology with various actions and scenarios that are scored such as speeding up on a linear road, slowing down on a curved road, and stopping in front of the stop traffic sign. • The recognition of traffic signs, facial expressions, and actions of the AI-FML Robot is also a scoring criterion.			



(a)

(b)

Fig. 14. Total points, travel time, and loss for students in (a) JCM 1 and JCM 2, (b) SCM 3 and SCM 4.

Table IV displays the information about the involved students and rules. Fig. 14(a)-(b) shows that senior high-school students perform better in practice-based and operation-based learning, as indicated by their higher total points, shorter travel time, and lower loss. Junior high-school students do not perform as well as senior high-school students in this type of learning.

E. *Constructed Models based on Data Collected*

We perform data cleaning, statistical analysis, and standardization on the original data collected from JCM 1 (257,394 records), JCM 2 (378,095 records), SCM 3 (181,896 records), and SCM 4 (1,657,023 records) to construct the KB and RB for the genetic assessment agent. As a result, the number of extracted knowledge concepts with four key features for JCM 1, JCM 2, SCM 3, and SCM 4 becomes 270 × 4=1,080, 225×4=900, 165×4=660, and 464×4=1,856, respectively. In this subsection, we use the data collected from SCM 4 as the training set to optimize the GFML and PFML models, following the algorithm listed in Table II. We adopt the mean square error (MSE) as the performance evaluation metric. In this subsection, we conducted five experiments (Exps. 1 to 5) and Table V shows the information on these experiments.

TABLE V. FIVE-EXPERIMENT INFORMATION.

Exp. 1: Utilize GA, PSO, and GANN to find the optimal model of students' learning state of SCM 4 using the same set of parameters for each method, where crossover rate (p_c) = 0.9, mutation rate (p_m) = 0.1, Generation No. (N_G) = 1000, and Solution No. (N_S) = 20.
Exp. 2: Compare the performance of GANN with different methods of selection (Exps. 2.1−2.12), crossover (Exps. 2.13−2.24), and mutation (Exps. 2.25−2.32) to find the optimal model, where p_c = 0.9, p_m = 0.1, N_G = 1000, and N_S = 20. In addition, the architecture of GANN is configured with an input layer with 4 nodes, two hidden layers with 12 nodes and 4 nodes, respectively, as well as an output layer with a node.
Exp. 3: Compare different hyper-parameter settings (p_c = 0.9 or 0.1) and p_m = 0.1 or 0.05) to tune the parameters of the GANN model for different numbers of generations N_G = 500 (Exp. 3.1), 1000 (Exp. 3.2), 2000 (Exp. 3.3), and 4000 (Exp. 3.4). The architecture of GANN is configured the same as **Exp. 2**.
Exp. 4: The best model of **Exp. 3** is adopted and changed by the number of nodes in two hidden layers of GANN to find the optimal model.
Exp. 5: The best model of **Exps. 1 to 4** is adopted to predict the students' learning state in JCM 1, JCM 2, and SCM 3.

In **Exp. 1**, Table VI displays the MSE values obtained using roulette wheel selection, single-point crossover, and random mutation. It can be seen that a direct comparison of GA, PSO, and GANN using the same parameters shows that the use of GANN resulted in the lowest MSE and therefore performed best.

TABLE VI. SET OF PARAMETERS OF EACH METHOD AND MSE IN EXP. 1.

Method	Solution	p_c	p_m	N_G	*MSE*
GA	20	0.9	0.1	1000	0.00791
	20	0.6	0.1	1000	0.00772
PSO	20	N/A	N/A	1000	0.009
GANN	20	0.9	0.1	1000	0.00695
	20	0.6	0.1	1000	0.00603

In **Exp. 2**, we varied the parameters of GANN as follows: 1) selection types including steady-state selection, roulette wheel selection, stochastic universal selection, rank selection, random selection, and tournament selection; 2) crossover types including single-point crossover, two-point crossover, uniform crossover, and scattered crossover; 3) mutation types including random mutation, swap mutation, inversion mutation, and scramble mutation. The total number of sub-experiments was originally 96, but we found that changing the mutation type to swap, inversion, or scramble resulted in higher MSE values than the random type. Therefore, we excluded all combinations that involve swap, inversion, or scramble mutation, resulting in a reduced number of sub-experiments to 32. Fig. 15 and Fig. 16 show the MSE curves and bar charts when setting the mutation method to random, but varying the selection and crossover methods, respectively. Although scattered crossover had the lowest MSE when using rank selection, it was found to be not stable. Hence, the best model was found to be the one trained with random selection, two-point crossover, and random mutation.

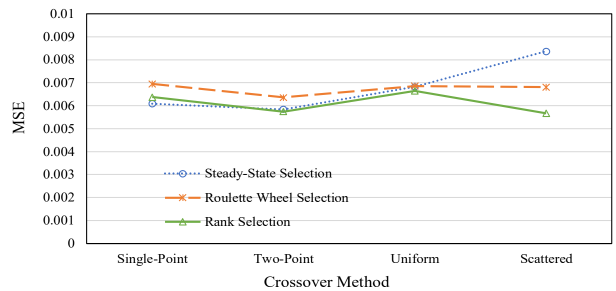


Fig. 15. MSE curves when setting the mutation method to random, but varying the selection and crossover methods.

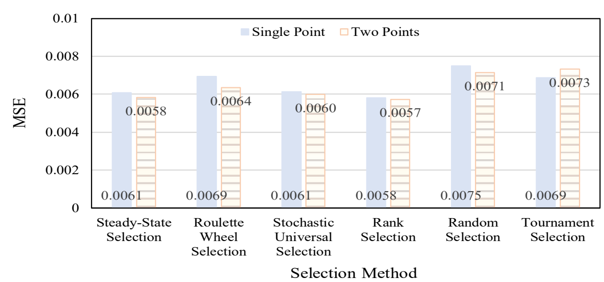


Fig. 16. MSE bar chats when setting the mutation method to random, but varying the selection and crossover methods.

For **Exp. 3**, we employed a rank selection, two-point crossover, and random mutation techniques based on the outcomes of **Exp. 2**. We conducted N_G = 500, 1000, 2000, and 4000 per setting while varying the p_c and p_m parameters to facilitate comparison and analysis. Fig. 17 displays the bar charts of MSE, which reveal that the combination of (0.6, 0.05) with N_G = 500 yields the best performance. In Fig. 18, we present the evaluation times for each setting. The most time-consuming one occurs for (0.6, 0.05) with N_G = 4000, taking a total of approximately 1628 seconds (27 minutes).

In **Exp. 4**, we used the best parameters from **Exp. 3** to vary the architecture of GANN by testing the following configurations: 4-4-1 (one hidden layer with 4 nodes), 4-12-4-1 (two hidden layers with 12 nodes and 4 nodes, respectively), and 4-17-4-1 (two hidden layers with 17 nodes and 4 nodes, respectively). The results, shown in Table VII, indicate that the best architecture of GANN is the one with 4 input nodes, two hidden layers (12 nodes and 4 nodes), and 1 output node.

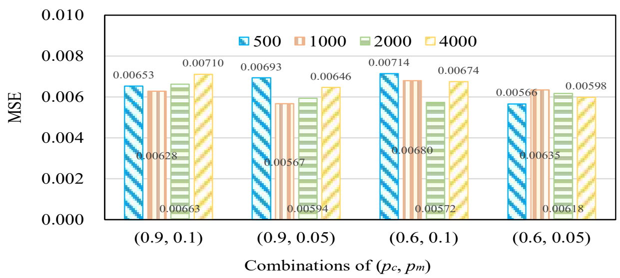


Fig. 17. MSE bar chats when varying different hyper-parameter settings.

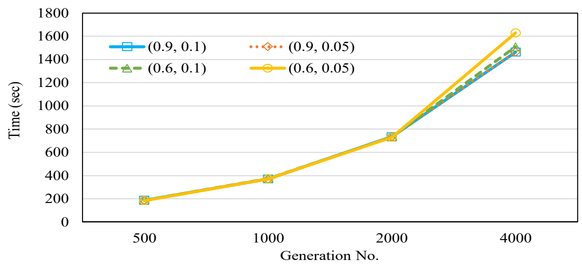


Fig. 18. Time-consuming curves when varying different hyper-parameter settings.

TABLE VII. THREE SETS OF PARAMETERS IN EXP. 4 AND RESULTS.

No.	Architecture of GANN	MSE	Best Generation No.
1	4-4-1	0.00721	488
2	4-12-4-1	0.00566	496
3	4-17-4-1	0.00612	395

In **Exp. 5**, we used the model trained with the following settings: rank selection, two-point crossover method, random mutation method, p_c = 0.6, p_m = 0.05, N_S = 20, N_G = 500, and GANN architecture with 4 nodes in the input layer, 12 nodes and 4 nodes in the first hidden layer and second hidden layer, respectively, and 1 node in the output layer. This model was used to predict the students' learning state in JCM 1, JCM 2, and SCM 3. Table VIII shows that JCM 2 had the best fit for the model.

TABLE VIII. PREDICTION RESULTS IN EXP. 5.

Course No.	MSE
JCM 1	0.03553
JCM 2	0.00424
SCM 3	0.00563

VI. CONCLUSION

In this study, we optimized the student and machine co-learning model for high school students' CI experience using EC techniques. To achieve this, we applied a genetic assessment agent to construct a human and machine co-learning model for CI learning. Then, we implemented the proposed agent practice in high school students' CI learning and undergraduate computer science learning during the Spring Semester of 2022 and collected data from four learning fields to evaluate and validate the state of the students involved using techniques of machine learning and NLP. Additionally, we adopted three mechanisms of evolutionary computation (GFML, PFML, and GANN) to train the model and predict the students' states of CI learning activities. From the experimental results, the genetic assessment agent with the GANN mechanism has better performance in the student and machine co-learning model and JCM 2 had the best fit with the model.

Our future aim is to enhance the capabilities of the agent to predict student learning states across various subjects, including CI. This will enable teachers to predict the learning state of students after a class or quiz, provide real-time assistance to those who are falling behind or ahead in their studies, and offer adaptive teaching materials to minimize learning setbacks. Additionally, we plan to gather more features to apply the agent in classifying students' states into different levels, such as reinforced, passable, good, or excellent.

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