International Journal on Advanced Science Engineering Information Technology

Vol.14 (2024) No. 5
ISSN: 2088-5334

A Comparative Study on the Performance of Algorithms on Different AI Platforms

Youngseok Lee [a], Jungwon Cho [b,*]

[a] *Department of Computer Education, Seoul National University of Education, 96 Seochojungang-ro, Seocho-gu, Seoul, Republic of Korea*
[b] *Department of Computer Education, Jeju National University, 102 Jejudaehakno, Jeju-si, Jeju-do, Republic of Korea*
*Corresponding author: *jwcho@jejunu.ac.kr*

***Abstract*—To understand the basic concepts and principles of artificial intelligence (AI) and to solve problems using AI, it is necessary to use various platforms. Among AI machine-learning (ML) models, the prediction algorithm is a basic AI model that can be used in various fields, such as for predicting weather, grades, product prices, and population, and is likely to be used to gain a basic understanding of AI. Many educational AI platforms implement prediction algorithms to help understand these AI models. In this study, prediction algorithms were implemented using the following AI platforms: Orange3, Entry, and Python to learn the temperature data in the Seoul area of Korea using a linear regression model, predict the value of temperature change, and evaluate the performance of the prediction algorithm for each platform. Additionally, to understand machine learning classification models and develop effective teaching methods, we conducted a prototype test to compare and analyze each platform's photo classification methods and performance. As a result of the comparison, Python exhibited the best performance, followed by Orange3 and Entry, with differences in accuracy and predicted values. To understand AI, it is necessary to understand the reliability of AI models and use an appropriate platform that considers the development level of the learner. In the future, we aim to research different ways to efficiently understand AI by comparing and analyzing its performance using various AI models.**

***Keywords*—Algorithms performance; AI platforms; machine learning models; AI algorithms; reliability of AI models.**

Manuscript received 7 Dec. 2023; revised 14 Apr. 2024; accepted 8 Aug. 2024. Date of publication 31 Oct. 2024.

I. INTRODUCTION

In 2020, the Ministry of Education announced the direction and key tasks of the education policy in the era of artificial intelligence (AI), presented the need to cultivate AI talent, and announced that it would gradually promote AI education from kindergarten to elementary, middle, and high school curricula in Korea [1]. We found that most countries focus on nurturing AI talent as a national policy by analyzing domestic and foreign AI education policies, such as those of the United States, China, and the United Kingdom. AI education has become an essential issue not only as a current trend but also from a policy perspective [2].

This type of AI education can be divided into AI understanding education, AI utilization education, and AI value education. AI-understanding education involves learning theories about AI knowledge, concepts, and algorithms and acquiring AI functions. Some studies define education [3]. Various platforms are used for AI education. As a data analysis platform for AI education, 12 platforms that use machine learning for Kids, Entry, Teachable Machine, Orange3, and mBlock were compared. Moreover, Python research is being conducted on lesson design to help easily understand AI and deep learning [4]–[6]. This study focuses on data literacy, which is essential in AI education, and algorithms, which are important learning elements for understanding and utilizing AI in any field. We provide AI education without programming using AI education platforms presented in previous studies.

We selected Orange3, Entry (a block programming form), Teachable Machine, and Python (a text-programming form). Among the algorithms commonly available on these four platforms, we selected a linear regression (prediction) algorithm that can be used to make predictions in various real-life scenarios, such as temperature, population, product prices, and grades. We learned it by analyzing the temperature data in Seoul. Subsequently, we created a simple temperature change prediction model and determined each platform's performance to estimate its reliability and usability for comparison.

II. Materials and Methods

As technological innovations using AI develop rapidly and influence various fields of society, the government emphasizes the need for AI education. It seeks to change education by building a system that allows customized learning based on occupation and life cycle [7]–[9]. The Ministry of Education has also emphasized AI education in Korea and established achievement standards to explore the types and forms of data that can be used for AI in elementary school classroom curricula and to experience creating [10]–12]. Recently, some studies have investigated the current status of AI education in schools worldwide. Most curricula include fundamental concepts and theories, coding, and application development, but education on AI's ethics and social responsibility still needs to be improved [13].

In AI education, information utilization skills are paramount. AI education enhances students' abilities to collect and analyze information, which, in turn, helps them develop problem-solving skills [14]. Through AI education, students learn how to gather and analyze data effectively. Data analysis is crucial for students to understand and use information. AI education offers various methods for visualizing and analyzing data using specialized tools and programs, enhancing students' problem-solving abilities [15]. AI education equips students with problem-solving capabilities essential for future societies by supporting students in learning these skills.

Incorporating AI education into the school curriculum is essential for teaching students how to utilize AI effectively [16]. For example, students can learn to automate tasks using AI technology or solve problems with AI. Some research examined the experiences, strategies, and challenges faced by teachers who introduced AI education in elementary schools. The study also discussed making AI concepts and theories accessible to young students and evaluated the appropriateness of different learning methods using AI. Overall, synthesizing research on AI education trends in schools suggests that AI education significantly strengthens creative thinking. Using AI technology to solve new problems fosters innovative thinking, making it necessary to support students experimenting with various methods to tackle new challenges [17].

The importance of AI education is increasing, and various studies are being conducted on ways to utilize AI education platforms. One study suggested that the development plan for an AI education platform should focus on AI-related knowledge (theory, experience, ethics, etc.) and practice (machine learning) and include various functions necessary for machine learning practice [18]. A study on the perception of class content using an AI education platform found that middle school teachers who deal with algorithms perceived the algorithm guidance used for learning AI model design, training, and analysis to be more critical [19].

Thus, when training AI, deriving results by applying AI models to the database platform based on data is crucial to understanding AI. However, if it is difficult to determine the accuracy of data analysis, it will be challenging to trust and utilize the AI model [20]. In other words, determining whether the results obtained in AI education can be trusted is essential for using the analysis results in the subsequent AI utilization for problem-solving [21]–[22].

The study utilized Orange3's user-friendly, drag-and-drop interface to introduce data visualization techniques to students with minimal programming background [23]. To assess the impact of data visualization education using Orange3 on students' comprehension of data analysis. It focused on simplifying data analysis through graphical tools. Students improved their understanding of data structures and their ability to interpret data visually, enhancing their analytical thinking. The study noted that Orange3's capabilities are limited in advanced data analysis and machine learning tasks, restricting its use for higher-level AI education.

Research examines the relationship between AI education and improved programming skills using Python [24]. Python was introduced to high school students as a tool for teaching foundational AI concepts, including simple algorithms and machine learning techniques. Python libraries such as NumPy and pandas were used for practical exercises. The students demonstrated a marked improvement in programming proficiency, logical reasoning, and problem-solving abilities. They also gained a solid understanding of AI's foundational principles. The research identified challenges in engaging students with no coding experience, highlighting the need for additional support in foundational programming concepts.

There is research to improve elementary school students' AI Concepts using Orange3 [25]. Orange3's visual, block-based interface introduced fundamental AI concepts, allowing students to experiment with simple data flows and machine learning models without writing code. Using hands-on learning approaches, students could grasp the basic ideas behind AI, such as data input/output and pattern recognition. The simplicity of Orange3 limited the depth of AI education, as more advanced topics could not be effectively covered at this educational level.

The study discussed improving AI Literacy through Python-based education in higher education [26]. To examine the effectiveness of Python in enhancing AI literacy among university students, the study integrated Python with AI-related libraries such as scikit-learn and TensorFlow to teach machine learning and deep learning concepts. Students participated in both theoretical lectures and practical coding assignments. Integrating Python in AI education significantly improved students' understanding of AI theory and application. They also developed valuable skills in model building and data analysis. The study highlighted the difficulty some students faced in comprehending complex algorithms, especially those with limited programming or mathematical backgrounds.

There is a case study comparing Orange3 and Python in AI Education. Orange3 was used for introductory lessons on data manipulation and simple machine learning tasks, while Python was employed for more complex tasks such as neural networks and natural language processing. Orange3 provided an accessible introduction to AI, while Python allowed a more in-depth exploration of advanced concepts. Students were able to transition from visual learning to coding-based problem-solving. They developed a machine learning workflow to achieve high classification accuracy and improved prediction confidence using binary classification on a public dataset from a Portuguese financial institution as a proof of concept [27].

In this study, we analyzed data using an AI education platform and compared the performance of each platform to confirm its reliability and educational usability.

III. Results and Discussion

This study seeks to compare and analyze the same data using Orange3, Entry, and Python AI programming language platforms using a prediction algorithm with linear regression.

A. Orange3

Orange3 is a widget-type platform that can analyze data such as images, letters, and numbers using various AI models such as linear regression, SVM (Support Vector Machines), logistic regression, neural networks, and KNN. Even users unfamiliar with programming can efficiently perform ML and data visualization [28]–[30]. Fig. 1 illustrates the steps in learning the data processing workflow to derive insights using Orange3 without programming.

Data preprocessing is essential to predict temperature and humidity. Effective data preprocessing is a critical step in AI training. For the AI algorithm to function appropriately, data such as temperature, precipitation, and humidity recorded by date must be transformed into annual data, ensuring consistency across the exact dates. This allows the prediction algorithm to work effectively.

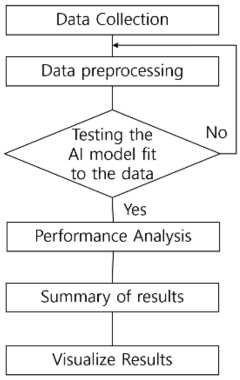
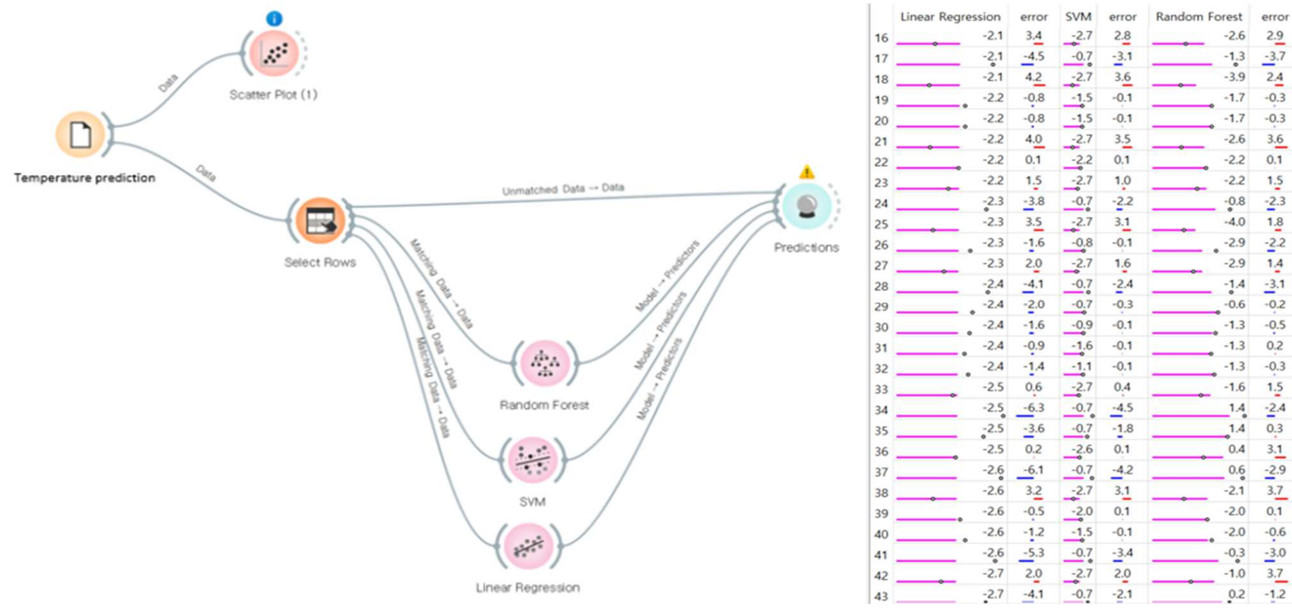


Fig. 1 Data processing process

Fig. 2 and Table 1 show a screen that uses Orange3 to implement Seoul’s average temperature data from 1973 to 2021 as a linear regression (prediction) model. The data sampler set the learning and test data to 70% and 30%, respectively, with the year as the feature and the average temperature as the target. The number of epochs, batches, and learning rate could not be determined or analyzed according to the optimization values set in the platform's linear regression model. The data were visualized using a scatterplot, and the analysis results yielded an R2 value of 0.011.



	Linear Regression	error	SVM	error	Random Forest	error
16	-2.1	3.4	-2.7	2.8	-2.6	2.9
17	-2.1	-4.5	-0.7	-3.1	-1.3	-3.7
18	-2.1	4.2	-2.7	3.6	-3.9	2.4
19	-2.2	-0.8	-1.5	-0.1	-1.7	-0.3
20	-2.2	-0.8	-1.5	-0.1	-1.7	-0.3
21	-2.2	4.0	-2.7	3.5	-2.6	3.6
22	-2.2	0.1	-2.2	0.1	-2.2	0.1
23	-2.2	1.5	-2.7	1.0	-2.2	1.5
24	-2.3	-3.8	-0.7	-2.2	-0.8	-2.3
25	-2.3	3.5	-2.7	3.1	-4.0	1.8
26	-2.3	-1.6	-0.8	-0.1	-2.9	-2.2
27	-2.3	2.0	-2.7	1.6	-2.9	1.4
28	-2.4	-4.1	-0.7	-2.4	-1.4	-3.1
29	-2.4	-2.0	-0.7	-0.3	-0.6	-0.2
30	-2.4	-1.6	-0.9	-0.1	-1.3	-0.5
31	-2.4	-0.9	-1.6	-0.1	-1.3	0.2
32	-2.4	-1.4	-1.1	-0.1	-1.3	-0.3
33	-2.5	0.6	-2.7	0.4	-1.6	1.5
34	-2.5	-6.3	-0.7	-4.5	1.4	-2.4
35	-2.5	-3.6	-0.7	-1.8	1.4	0.3
36	-2.5	0.2	-2.6	0.1	0.4	3.1
37	-2.6	-6.1	-0.7	-4.2	0.6	-2.9
38	-2.6	3.2	-2.7	3.1	-2.1	3.7
39	-2.6	-0.5	-2.0	0.1	-2.0	0.1
40	-2.6	-1.2	-1.5	-0.1	-2.0	-0.6
41	-2.6	-5.3	-0.7	-3.4	-0.3	-3.0
42	-2.7	2.0	-2.7	2.0	-1.0	3.7
43	-2.7	-4.1	-0.7	-2.1	0.2	-1.2

Fig. 2 Data analysis using Orange3

TABLE I
PREDICTION MODEL TEST RESULTS ACCORDING TO ALGORITHM USING ORANGE3

Model	MSE	RMSE	MAE	MAPE	R^2
Linear regression	13.799	3.715	3.119	1.858	0.011
SVM	9.248	3.041	2.225	0.816	0.337
Random Forest	5.207	2.282	1.827	1.032	0.627

B. Entry

Entry is a platform widely used in elementary education because it can be programmed using block programming and has excellent scalability. It can implement AI models using data analysis and AI blocks. The AI blocks that can be used in Entry are primarily divided into two areas: AI utilization blocks (translation, video detection, audio detection, and reading) and AI model learning blocks (AI learning models including KNN, SVM, linear regression, and logistic regression).

Fig. 3 shows a screen that uses Entry to learn Seoul’s temperature data mentioned earlier as a linear regression (prediction) model. Similar to Orange 3, one can quickly create an AI model. However, unlike Orange 3, Entry allows one to set the number of epochs, batches, learning ratio, and verification data ratio when training the model. The number of epochs, number of batches, and learning rate were left at default values of 30, 16, and 0.03, respectively, and only the verification data ratio was set at 0.3, making the learning and test data 70% and 30%, respectively, same as those for Orange3.

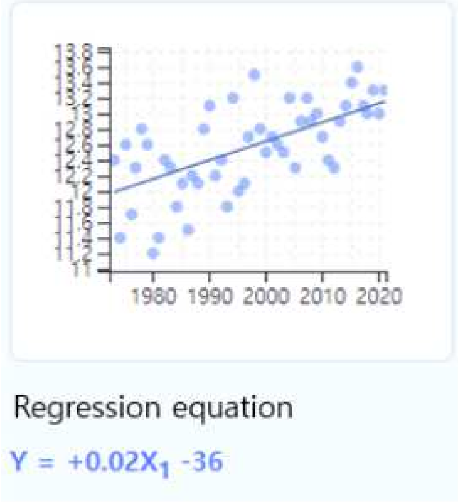


Fig. 3 Learning AI model using Entry

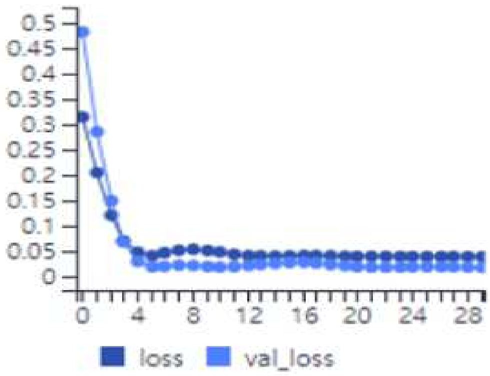


Fig. 4 The loss results of linear regression model

After learning the AI model, block coding was performed on the Entry coding screen, as shown in Fig. 4 to check the model, data visualization analysis, and prediction results. The coefficient of determination of the regression (prediction) model, as confirmed by block programming, was 0.57. Notably, if the verification data ratio was set as the default value of 0.25, the coefficient of determination increased to 0.61.

C. Python

Python is a coding platform that uses a programming language that provides various libraries, such as ML models and data visualization, to implement AI models. Because Python is relatively easy for beginners to learn, students can use it. The data must first be preprocessed into a multidimensional array to use a linear regression model in Python. The goal is to create a model that optimizes the input vector X to predict the target value y by constructing a linear regression function. This process helps students understand data preprocessing and AI models and allows them to apply the model to their data.

In a Python linear regression model, to check the slope and intercept of the resulting line, you must examine the feature values' slope and y-intercept. You can then evaluate the model's accuracy using the score function to determine how well these values predict y based on the input X. The data mentioned earlier were analyzed using a linear regression (prediction) model in Python. The LinearRegression class in Python's Scikit-Learn package was used. The year was specified as train_feature, and the average temperature was specified as train_target.

Before training, using the train_test_split() function, test_size was set to 0.3 to maintain the training and test dataset sizes of 70% and 30%, respectively. Moreover, random_state was set to 0. After learning, the model performance of 0.70 was obtained using the lr.score() function. The results, visualized in a graph comparing the predicted and actual values, are illustrated in Fig. 5.

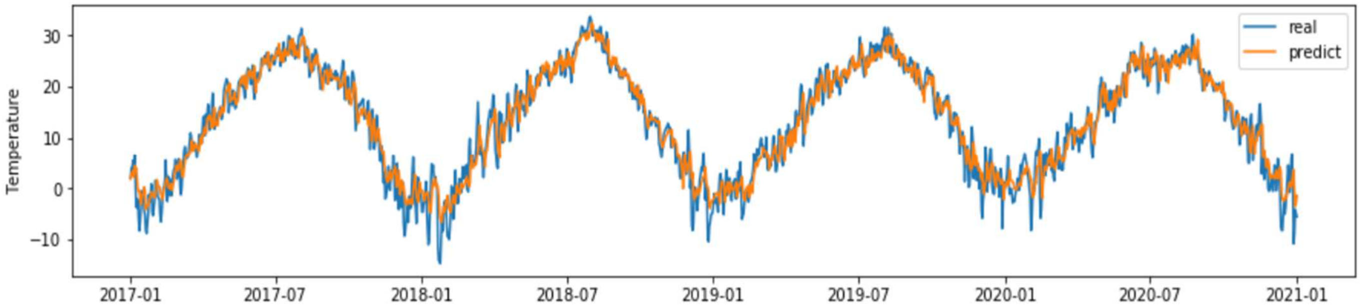


Fig. 5 Results of Python linear regression prediction model

D. Comparison of data prediction results

Using Seoul's annual average temperature data from 1908 to 2017 (excluding data from 1950 to 1953), the three platforms were trained to obtain a linear regression (prediction) model, which was then used to calculate the average temperature data for Seoul in the same period. Table 2 lists the differences between the predicted and actual values of Seoul's average annual temperature up to 2018.

TABLE II
COMPARISON OF DATA PREDICTION RESULTS

Year	Actual value	Predicted value (difference)		
		Orange3	Entry	Python
2018	12.9	13.2(▲0.3)	12.48(▼0.42)	13.2(▲0.3)
2019	13.5	13.2(▼0.3)	12.5(▼1)	13.23(▼0.27)
2020	13.2	13.3(▲0.1)	12.52(▼0.68)	13.26(▲0.06)
2021	13.7	13.3(▼0.4)	12.54(▼1.16)	13.28(▼0.42)
2022	13.2	13.3(▲0.1)	12.55(▼0.65)	13.31(▲0.11)

Python exhibits the most negligible difference from the actual average temperatures. The model created with Orange3 yielded the same predicted value of 13.2°for 2018 and 2019 and 13.3° for 2020-2022. As such, there was little change in the expected value by year. However, compared to the actual temperature, it predicted the next closest value after Python. The Entry showed a significant difference between the predicted and actual values compared to Orange3 and Python.

E. Comparison of Image Data Classification Results

Many elementary school students tend to draw casually and play during class, which makes it difficult to distinguish between those who are putting in effort and those who are not. This inconsistency needs to be clarified for evaluating students' engagement in art activities. To address this challenge, we identified the need for an automated system to assess artwork effectively. As a result, we conducted a case study to develop a simple automation system using a webcam, leveraging an artificial intelligence algorithm to facilitate this process.

To analyze the performance of the image classification results, pass and fail were judged based on images drawn by elementary school students. The image data included 54 failed images, 56 passed images, and 7 test images. The algorithm for Orange3 is written in Python, so the performance is the same. Table 3 shows the results of comparing the performance of the AI algorithms. In Orange 3, the Logistic regression algorithm had a % classification accuracy of 71.8%. The classification accuracy of the teachable machine was the same, 71.4%, and the accuracy of Entry's kNN (K-nearest neighbors) algorithm was 57.1%.

TABLE III
COMPARISON OF AI ALGORITHM PERFORMANCE RESULTS

Model	AUC	CA	F1	Prec	Recall	MCC
Logistic Regression	.749	.718	.718	.718	.718	.436
Neural Network	.730	.709	.709	.709	.709	.418
SVM	.704	.700	.700	.700	.700	.400
kNN	.609	.555	.542	.558	.555	.109
Naïve Bayes	.648	.609	.609	.611	.609	.220
Random Forest	.629	.627	.625	.632	.627	.260

The teachable machine performs better in image classification; however, there was little difference when preprocessing students' images with Orange3. Due to the extended processing time required for Python's logistic regression algorithm when using a webcam, we opted for the Entry system, which has a relatively low accuracy of 57.1%, for actual image classification of student work. As a result, 4 out of 5 students successfully passed on their first attempt, while the remaining students passed on their third attempt. When asked if they would participate in the AI test during class to create additional artwork, all five students were willing to try again, citing that it was enjoyable.

When prompted to share their thoughts, many students remarked on how fun the experience was. They expressed amazement that the system could identify mistakes, likening it to a human judging their accuracy. This case study demonstrates that image classification algorithms and AI models can effectively be utilized in various classroom settings. Therefore, it is essential to conduct diverse case studies that explore the application of AI models in different environments based on the performance of the AI platform to analyze meaningful results.

IV. CONCLUSION

This study attempted to compare whether the three platforms used in AI education, Orange3, Entry, and Python, are suitable for educational use by comparing their performances when implementing a linear regression (prediction) model. Accordingly, the same data were analyzed using a linear regression (prediction) model for each platform, and meaningful results were obtained through performance measurement and prediction results. Python exhibited the highest performance at 0.718, followed by teachable machine at 0.71 and Entry at 0.57. The predicted data values for Python were also slightly different from the actual values, and the gap gradually widened in that order, followed by Orange 3 and Entry.

As a result of the analysis, if one needs to use a linear regression (prediction) model, it would be better to use Python, which has the highest performance; however, elementary school students who are not familiar with programming may have some difficulty learning using Python. Because all three platforms achieved an accuracy rate of over 50%, we believe there will be plenty of educational use for students. Therefore, using an appropriate platform that considers students' development levels would be effective.

However, because some factors could not be controlled in terms of adjusting details, such as the number of epochs, batches, and learning rate for each platform, there were limitations in matching the conditions perfectly, and the model was implemented by matching only the ratio of training data to test data. Moreover, the fact that model performance values were compared after testing can be considered a limitation of this study.

In the future, we aim to compare the performance when using various AI models, such as CNN and RNN, in addition to multiple linear regression (prediction) and logistic regression models, to select the optimal AI platform that will be reliable and suitable for the algorithm design of the AI model.

REFERENCES

[1] E. Y. Lee, "A comparative analysis of contents related to artificial intelligence in national and international K-12 curriculum", *The Journal of Korean Association of Computer Education*, vol. 23, no. 1, pp. 37-44, 2020.

[2] C. Guan, J. Mou, and Z. Jiang, "Artificial intelligence innovation in education: A twenty-year data-driven historical analysis," *International Journal of Innovation Studies*, vol. 4, no. 4, pp. 134–147, Dec. 2020, doi: 10.1016/j.ijis.2020.09.001.

[3] S. Kim, S. Kim, M. Lee, & H. Kim, "Review on Artificial Intelligence Education for K-12 Students and Teachers," *The Journal of Korean Association of Computer Education*, 23(4), pp. 1-11, 2020.

[4] L. Chen, P. Chen, and Z. Lin, "Artificial Intelligence in Education: A Review," *IEEE Access*, vol. 8, pp. 75264–75278, 2020, doi:10.1109/access.2020.2988510.

[5] T. Siddiqui and M. Mustaqeem, "Performance evaluation of software defect prediction with NASA dataset using machine learning techniques," *International Journal of Information Technology*, vol. 15, no. 8, pp. 4131–4139, Oct. 2023, doi: 10.1007/s41870-023-01528-9.

[6] A. Alsaber et al., "Evaluation of various machine learning prediction methods for particulate matter $$PM_{10}$$ in Kuwait," *International Journal of Information Technology*, vol. 15, no. 8, pp. 4505–4519, Oct. 2023, doi: 10.1007/s41870-023-01521-2.

[7] X. Zhai et al., “A Review of Artificial Intelligence (AI) in Education from 2010 to 2020,” *Complexity*, vol. 2021, no. 1, Jan. 2021, doi:10.1155/2021/8812542.

[8] P.-H. Lin and S.-Y. Chen, “Design and Evaluation of a Deep Learning Recommendation Based Augmented Reality System for Teaching Programming and Computational Thinking,” *IEEE Access*, vol. 8, pp. 45689–45699, 2020, doi: 10.1109/access.2020.2977679.

[9] Seol-Ah Min, In-Seong Jeon, Ki-Sang Song, “The Effects of Artificial Intelligence Convergence Education using Machine Learning Platform on STEAM Literacy and Learning Flow,” *Journal of the Korea Society of Computer and Information*, 26(10), pp. 199-208, 2021.

[10] T. K. F. Chiu, “A Holistic Approach to the Design of Artificial Intelligence (AI) Education for K-12 Schools,” *TechTrends*, vol. 65, no. 5, pp. 796–807, Aug. 2021, doi: 10.1007/s11528-021-00637-1.

[11] A. K. Dubey, A. K. Sinhal, and R. Sharma, “Heart disease classification through crow intelligence optimization-based deep learning approach,” *International Journal of Information Technology*, vol. 16, no. 3, pp. 1815–1830, Sep. 2023, doi: 10.1007/s41870-023-01445-x.

[12] A. R. Shibli, N. Fatima, M. Sarim, N. Masroor, and K. Bilal, “Machine learning-based predictive modeling of student counseling gratification: a case study of Aligarh Muslim University,” *International Journal of Information Technology*, vol. 16, no. 3, pp. 1909–1915, Nov. 2023, doi: 10.1007/s41870-023-01620-0.

[13] I. García-Martínez, J. M. Fernández-Batanero, J. Fernández-Cerero, and S. P. León, “Analysing the Impact of Artificial Intelligence and Computational Sciences on Student Performance: Systematic Review and Meta-analysis,” *Journal of New Approaches in Educational Research*, vol. 12, no. 1, pp. 171–197, Jan. 2023, doi:10.7821/naer.2023.1.1240.

[14] B. Williamson and R. Eynon, “Historical threads, missing links, and future directions in AI in education,” *Learning, Media and Technology*, vol. 45, no. 3, pp. 223–235, Jul. 2020, doi:10.1080/17439884.2020.1798995.

[15] I. Lee and B. Perret, “Preparing High School Teachers to Integrate AI Methods into STEM Classrooms,” *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 36, no. 11, pp. 12783–12791, Jun. 2022, doi: 10.1609/aaai.v36i11.21557.

[16] T. N. Fitria, “Artificial intelligence (AI) in education: Using AI tools for teaching and learning process”, *prosenas*, vol. 4, no. 1, pp. 134–147, Dec. 2021.

[17] J. M. Górriz et al., “Artificial intelligence within the interplay between natural and artificial computation: Advances in data science, trends and applications,” *Neurocomputing*, vol. 410, pp. 237–270, Oct. 2020, doi: 10.1016/j.neucom.2020.05.078.

[18] P. Gao, J. Li, and S. Liu, “An Introduction to Key Technology in Artificial Intelligence and big Data Driven e-Learning and e-Education,” *Mobile Networks and Applications*, vol. 26, no. 5, pp. 2123–2126, Apr. 2021, doi: 10.1007/s11036-021-01777-7.

[19] I. Lee, S. Ali, H. Zhang, D. DiPaola, and C. Breazeal, “Developing Middle School Students’ AI Literacy,” *Proceedings of the 52nd ACM Technical Symposium on Computer Science Education*, pp. 191–197, Mar. 2021, doi: 10.1145/3408877.3432513.

[20] I. Mishra and S. Mohapatra, “An enhanced approach for analyzing the performance of heart stroke prediction with machine learning techniques,” *International Journal of Information Technology*, vol. 15, no. 6, pp. 3257–3270, Jun. 2023, doi: 10.1007/s41870-023-01321-8.

[21] B. Singh and R. Jaiswal, “Automation of prediction system for temporal data,” *International Journal of Information Technology*, vol. 14, no. 6, pp. 3165–3174, Aug. 2022, doi: 10.1007/s41870-022-01065-x.

[22] A. Das, D. Choudhury, and A. Sen, “A collaborative empirical analysis on machine learning based disease prediction in health care system,” *International Journal of Information Technology*, vol. 16, no. 1, pp. 261–270, Oct. 2023, doi: 10.1007/s41870-023-01556-5.

[23] G. A. Özkök, “Fostering Computational Thinking Through Data Visualization and Design on Secondary School Students,” *JUCS - Journal of Universal Computer Science*, vol. 27, no. 3, pp. 285–302, Mar. 2021, doi: 10.3897/jucs.66265.

[24] R. M. Martins and C. Gresse Von Wangenheim, “Findings on Teaching Machine Learning in High School: A Ten - Year Systematic Literature Review,” *Informatics in Education*, Sep. 2022, doi: 10.15388/infedu.2023.18.

[25] J. Son and T. Kim, “The Effectiveness of the Living Lab-based Elementary School Data Science Program,” *Journal of The Korean Association of Information Education*, vol. 26, no. 2, pp. 105–120, Apr. 2022, doi: 10.14352/jkaie.2022.26.2.105.

[26] J. Hutson et al., “Artificial Intelligence and the Disruption of Higher Education: Strategies for Integrations across Disciplines,” *Creative Education*, vol. 13, no. 12, pp. 3953–3980, 2022, doi: 10.4236/ce.2022.1312253.

[27] A. Aldelemy and Raed A. Abd-Alhameed, “Binary Classification of Customer’s Online Purchasing Behavior Using Machine Learning,” *Journal of Techniques*, vol. 5, no. 2, pp. 163–186, Jun. 2023, doi: 10.51173/jt.v5i2.1226.

[28] Z. Dobesova, “Evaluation of Orange data mining software and examples for lecturing machine learning tasks in geoinformatics,” *Computer Applications in Engineering Education*, vol. 32, no. 4, Mar. 2024, doi: 10.1002/cae.22735.

[29] A. Arabiat and M. Altayeb, “Enhancing internet of things security: evaluating machine learning classifiers for attack prediction,” *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 14, no. 5, p. 6036, Oct. 2024, doi: 10.11591/ijece.v14i5.pp6036-6046.

[30] A. Arabiat and M. Altayeb, “An automated system for classifying types of cerebral hemorrhage based on image processing techniques,” *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 14, no. 2, p. 1594, Apr. 2024, doi: 10.11591/ijece.v14i2.pp1594-1603.