Using Convolutional Neural Network to Assist Teachers Detecting Test Sheet Cognition Level

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Abstract. This study used convolutional neural network in machine leaning techniques to detecting test sheet cognition level for assisting teachers. Particularly, this study would like to use the paint algorithm procedure with the analysis feedback, instructors can provide suggestions to improve their examination. We provide six types of results based on students' ages and cognitive levels. Instructors can adjust their assessment and examination styles accordingly. In convolutional neural network to implement the polling layer action, there are two methods, one is “Max Pooling”, and the other is “Average Pooling”. Basically, we select “Max Pooling” to present the most significant feature.

Keywords: Machine Leaning; Convolutional Neural Network; Detecting Test Sheet, Cognition

1 Introduction

Due to the widespread use of distance learning, learning resources and group communication are now commonly available on the internet and other wireless environments. Whether in a remote learning setting or a traditional classroom, teaching, and evaluation work in tandem as part of a complete learning cycle. However, an instructor may overlook certain crucial elements of a course when creating an examination. Conversely, examinations play a vital role in the learning cycle. For instance, if students take a pretest before preparing for a posttest based on the pretest examination paper, a sound assessment system offers a suitable means of gathering student feedback. By analyzing the results of the assessment, the teacher can adjust their teaching strategy, and if needed, redesign or reorganize learning materials. Moreover, the analysis of the assessment also helps students grasp the key points of the learning materials. Through assessment analysis, learners can identify the most critical elements of each subject and course on an individual basis. With the assistance of machine leaning algorithm, detecting test sheet cognition level balancing becomes more easily.

2 Related Works

Artificial intelligence is becoming a popular topic in computer science and information engineering department or information management department. AI is popular used in many aspects of applications. Berenguel PO, et. al. (2023) [1] invented an artificial neural networks (ANN) model for the characterization of microalgae cultures. Chang W.C. (2023) [2] using machine learning clustering theory in social network analysis, which promoted the learning performance in university programming course. It becomes very important to develop artificial intelligence in engineering courses.

The adaptive learning is an important research area for educational systems which aim to improve the outcomes of students. Everton Gomede et al. (2021) [3] compared three classes of Deep Auto Encoders and the popularity model to address the problem of learning and predicting the preferences of student. The results point out that the DAE-CF is more effective providing significant adaptability. In 2021, Joanne Wai Yee Chung et al. [4] using the (heart rate variability) HRV measures model correctly identified sadness. This research provided an objective method to assess the emotions have 239 participated. The inclusion criteria for selecting participants were healthy adults in local community with no known medical diagnosis. In 2021, Dechawut Wanichsan et al. [5] proposed a multi-expert testing and diagnostic learning system based on the concept-effect relationship model. It proposes a new method for integrating weighting values obtained from multiple experts for each concept's associated test item, considering the degree of confidence in decision-making.

Giuseppina Polito, and Marco Temperini (2021) [6] developed a web-based system called 2TSW that supports automated correction of computer programming tasks in a gamified environment. The system provides timely feedback to learners' solutions and increases motivation and engagement on programming activities. A systematic review of highly cited research papers related to chatbots and human behavior by Ke Zhang, and Ayse Begum Aslan (2023) [7] It explores the latest changes in chatbot research and highlights the potential of chatbots in education and online communication. The review shows that existing research has focused on high-level statistical performance and system development and testing.

Venkat Srinivasan, Hemavathi Murthy (2021) [8] using an AI-based multisensory technology platform across a large cross-section of government schools in India. The study focused on reading and comprehension in the English language. The intervention enhances the instructional effectiveness of the teachers and the learning ability of the children within the existing instructional environment without any new instructional design or pedagogy or content. An interactive test dashboard with diagnosis and feedback mechanisms to assist students' learning. C.-M. Chen et al. (2021) [9] found that the use of this dashboard significantly improved the learning performance, physics self-efficacy, and technology acceptance of students. The ITD-DFM provides more benefit in promoting the technology acceptance of learners with high prior knowledge level.

Lu Zheng et al. (2023) [10] the use of evolutionary algorithms and machine learning to build a smart education big data platform. The platform includes a personalized course recommendation model that uses deep belief networks and swarm intelligence evolutionary algorithms to recommend relevant content based on the interests of learners. this method with other methods on a public dataset to show the model's performance. Muhammad Zahid Iqbal, and Abraham G. Campbell (2023) [11] uses machine learning agents to facilitate kinesthetic learning in STEM education through touchless hand interaction. The approach aims to give teachers more agility in their teaching without replacing them.

There are some researches proposed the automatically cognitive analysis for test sheets or test items. Sarang Shaikh et. al. [12] proposed LSTM based deep learning model to classify the assessment items in Bl oom cognitive domain. Yuheng Li, et. al. [13] used naive Bayes, logistic regression, support vector machine, random forest, and XGBoost and one deep learning approach based on pre-trained language model BERT to construct classifiers to automatically determine a learning objective's cognitive levels. Nazlia Omar et. al. [14] applied Natural Language Processing (NLP) techniques to identify important keywords and verbs, which may assist in the identification of the category of a question. Ifham M. [15] presented a method for automatically identifying questions using an Artificial Neural Network (ANN). Term Frequency - Inverse Document Frequency (TF-IDF) is used to derive the features from questions papers. These research emphasis the assessment text, our method provides the final stage to analysis the entire test sheet cognition distribution.

3 Main Method

The instructional objective is a vital component of teaching. When the instructional objective is clear, it guides teaching activities and evaluations precisely and effectively. Another important factor in education is cognition. Assuming that the learning content prepared by the instructor is appropriate for the learner, learning can be efficient. In our meta data model, we have included the cognition level to provide learners with information on the cognitive demands of the learning content.

Bloom proposed a taxonomy of educational objectives that consists of three domains: the cognitive domain, the psychomotor domain, and the affective domain [16,17,18,19]. The cognitive domain includes six categories, namely knowledge, comprehension, application, analysis, synthesis, and evaluation. Knowledge: This involves recalling fundamental and previously learned information or lessons, such as knowledge of the learning subject, as well as knowledge of dates, places, or events. Comprehension: When individuals understand certain concepts or information, they can translate this knowledge into new contexts. Application: Applying knowledge to real-life situations, such as using skills or knowledge to solve problems. Analysis: This involves recognizing concepts or ideas and understanding structures or organizations. Synthesis: Using existing ideas or components to create new ones. Evaluation: Based on evidence, making comparisons and analyses, and then drawing conclusions.

The Assessment System Analysis Model is proposed by Chang, W.C. et al. (2004) [20]. The comprehensive process of teaching can be divided into three parts:

teaching strategy, learning content, and assessment. Assessment, including questionnaires, tests, examinations, and quizzes, plays a crucial role in this model. Although teachers may use suitable teaching strategies and good learning content, it is challenging to know whether students have learned well or not. Conducting tests is the only way to understand their learning progress. By analyzing the test results, teachers can evaluate how well students have learned, what students need, and how learning content can be improved. A good assessment analysis model provides a blueprint for teaching.

On the teacher side, the assessment system should provide individual question statistics and analysis, as well as whole test statistics and analysis. On the student side, the system should provide auxiliary tests for practice and a hint system. On the system side, the assessment system should deliver auxiliary tests for practice and questionnaires to both students and teachers.

Item Analysis: Providing Feedback and Improving Learning Content

The individual question is the basic element of an examination, and the assessment system can find instructors' blind spots by using number representation and signal representation for analysis and statistics. Item Analysis is performed by comparing the proportion of learners who pass an item in contrasting criterion groups. The instructor can see the status of each question, and the model can provide suggestions from the test questions. Upper and lower criterion groups are selected from the extremes of the distribution. In a normal distribution, the optimum point at which these two conditions balance out is 27%.

The feedback from Item Analysis should be provided to both students and teachers, and it should serve as the basis for improving learning content. Additionally, it can improve the quality of questions formulated by teachers for tests or exams.

In 1939, Professor Kelly established that the ideal percentage for item analysis is 27%, with an acceptable range of 25-33% [21]. In this paper, we aim to define the 25% percentage in our system using the following steps:

(1) First, sort the students according to their scores in the exam.
(2) Second, define PH as the top 25% of students and PL as the bottom 25% of students.
(3) Third, count the number of correct answers and the percentage of correct answers for each student in the higher and lower groups for each question.
(4) Fourth, calculate the item difficulty index for each problem as P = (PH+PL)/2.
(5) Fifth, calculate the item discrimination index for each problem as D = PH - PL.
(6) Sixth, record the information in the following format: No: The question number PH: The higher 25% of students as the higher group PL: The lower 25% of students as the lower group D: The discrimination index P: The difficulty index

To make Item Analysis more accessible to people, we use signal presentation instead of number presentation. However, it can be challenging to identify the status. Therefore, we have defined four rules that automatically show the analysis result. In Table 1, we define the item attributes of a single problem. HA, HB, HC, HD, and HE represent the number of students in the high-score group who select answer A, B, C, D, and E, respectively. Similarly, LA, LB, LC, LD, and LE represent the number of students in the low-score group who select answer A, B, C, D, and E, respectively. Let us consider a common example where the number of students in the high-score group and low-score group is 20 each.

We have defined four rules to analyze the problems, which we introduce below:

Rule 1: If (LA|LB|LC|LD|LE)= 0, then the answer's allure is low.

For instance, if no student in the low-score group selects answer C, then we can conclude that the answer's allure is low.

Rule 2: N = {A, B, C, D, E}

If Answer N is correct, and HN<LN, then the answer is not well-defined.

Table 1. Problem attribite

	Option A	**Option B**	**Option C**	**Option D**	**Option E**
High-score group	HA	HB	HC	HD	HE
Low-score group	LA	LB	LC	LD	LE

Signal presentation is used instead of numerical presentation in item analysis, as it can be difficult for people to understand the analysis with numbers. However, identifying the status with signal presentation can also be challenging. To overcome this, four rules are defined to automatically show the analysis results. Table 1 defines the item attributes of a single problem, including the number of students in the high-score group who choose each answer option (HA, HB, HC, HD, and HE), and the number of students in the low-score group who choose each answer option (LA, LB, LC, LD, and LE).

The four rules are as follows:

Rule 1: If none of the low-score group students select an answer option, the answer's allure is low.

Rule 2: If the number of high-score group students who choose the correct answer is lower than the number of low-score group students who choose the correct answer, the answer is not well-defined.

Rule 3: If the low-score group students select each answer option equally, then they lack the concept related to the problem.

Rule 4: If the high-score group students select each answer option equally, then they also lack the concept related to the problem.

By applying these rules, the status of the test can be identified and recorded in Table 2. This information can be helpful in correcting improper questions in the examination and in evaluating the students' learning. For example, if the class size is 44 students, with 11 students in each of the high-score and low-score groups, and the correct answer to a question is C, the signal presentation status can be found in Table 2.

Table 2. Advice and suggestions about questions

Status	D (Discrimination)	Rule 1	Rule 2
Good	Higher than 0.3	N/A	N/A
Need modify	0.2~0.29	--	--
Eliminate or need modify	Lower than 0.19	N/A	N/A

Table 3. Two-way specification table

	Knowledge	Comprehension	Application	Analysis	Synthesis	Evaluation	
Concept 1	A1	B1	C1	D1	E1	F1	SUM(A1~F1)
…	…	…	…	…	…	…	
Concept n	Ai	Bi	Ci	Di	Ei	Fi	SUM(Ai~Fi)
	SUM(A1~Ai)	SUM(B1~Bi)	SUM(C1~Ci)	SUM(D1~Di)	SUM(E1~Ei)	SUM(F1~Fi)	

The individuals in the high-score group selected their answers as follows: Answer A - 0 people, Answer B - 0 people, Answer C - 10 people, and Answer D - 1 person. The low-score group's individuals chose their answers as follows: Answer A - 3 people, Answer B - 2 people, Answer C - 4 people, and Answer D - 2 people. Item analysis provides us with the following information:

PH = 10/11 = 0.91

PL = 4/11 = 0.36

D = PH - PL = 0.91 – 0.36 = 0.55 > 0.3.

According to Table 2, the signal will indicate P = (PH + PL)/2 = (0.91 + 0.36)/2 = 0.635. Although the problem does not comply with Rules 1-4, if D (PH - PL) is lower than 0.19, the problem should be eliminated or fixed.

Assessment System's Total Test Statistics and Analysis

Various aspects should be considered while presenting assessment analysis results. A total test analysis result can reveal the overall status of the students.

Figure Representation:

(1) Time (x-axis) and Number of Answered Questions (y-axis) figure: This figure shows if the test time is sufficient or not.

(2) Test Score (x-axis) and Degree of Difficulty (y-axis) figure: This figure illustrates the score and difficulty distribution.

(3) Cognition Level (x-axis) and Learning Content Subjects (y-axis) figure: This figure shows the cognition level, question number, and subject (refer to Table 3).

Definition:

(1) Bloom's proposed cognitive level comprises A to F mapping. For example, knowledge is A, and comprehension is B. Let X be a universal set, where X = {A, B, C, D, E, F}.

(2) The test's concepts are designated from 1 to I, such as Concept 1.

(3) A question belonging to the Knowledge cognitive level is designed from Concept 1. A1 is set to [TRUE] if there exists more than one question belonging to the Knowledge cognitive level in Concept 1; otherwise, A1 is set to [FALSE].

(4) SUM(Xi) is the sum of cognition level X's questions in Concept i. For instance, SUM(F3) = 3 means that there are three questions of the evaluation level in Concept 3.

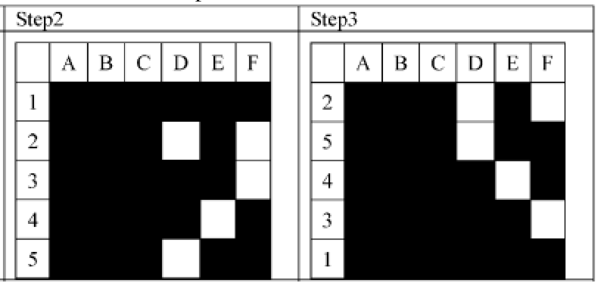
(5) The sum of questions in Concept i can be calculated using the formula SUM(Ai - Fi), where Ai represents the number of questions at the 'Knowledge' level and Fi represents the number of questions at the 'Evaluation' level. For instance, if SUM(A10-F10) = 8, it means there are eight questions ranging from the 'Knowledge' to the 'Evaluation' level in Concept 10.
(6) The sum of questions of the cognition level X, from Concept 1 to Concept i, can be calculated using the formula SUM(X1-Xi). For example, if SUM(C1 - C7) = 7, it indicates that there are seven questions ranging from Concept 1 to Concept 7.

Analysis:
(1) If (A1|B1|C1|D1|E1|F1)= FALSE, then it means that Concept 1 has been lost in the examination.
(2) There is a relation between the sum of questions and the cognition level. The formula is as follows: SUM(A1-Ai)>=SUM(B1-Bi) >=SUM(C1-Ci) >=SUM(D1-Di) >=SUM(E1-Ei)>=SUM(F1-Fi).
(3) The distribution of cognition levels and questions can be determined using the Paint algorithm (refer to Table 4). With the analysis feedback, instructors can provide suggestions to improve their examination. Table 5 provides six types of results based on students' ages and cognitive levels. Instructors can adjust their assessment and examination styles accordingly. In Table 5A, the test focuses on the 'Knowledge', 'Comprehension' and 'Application' cognition levels. In Table 5B, the test focuses on the 'Analysis', 'Synthesis' and 'Evaluation' cognition levels. In Table 5C, the test misses some concepts and the test key point is not the same as the teaching key point. In Table 5D, the test partially emphasizes some concepts and is inclined towards high cognition levels. In Table 5E, the test partially emphasizes some concepts and is inclined towards low-cognition levels. In Table 5F, the test's key point is too scattered, making it challenging for students to identify the main point.

Table 4. Paint alforithm procedure [20]

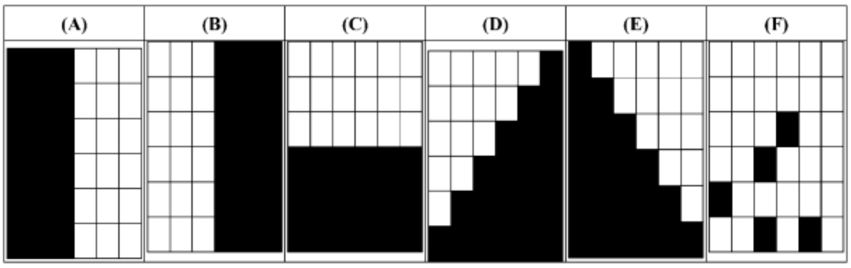
Step 1

	A	B	C	D	E	F
1	T	T	T	T	T	T
2	T	T	T	F	T	F
3	T	T	T	T	T	F
4	T	T	T	T	F	T
5	T	T	T	F	T	T



In step 1, if there is more than one question that belong to the "knowledge" cognition level exists in concept 1. A1 is [TRUE] to represent there is a question of "Knowledge" level in concept 1 at least. If A1 is false, there is no question of "Knowledge" level in concept 1. In step 2, If Xi is [TRUE], paint the block black. If Xi is [FALSE], paint the block white. In step 3, according to the number of black blocks in concept levels, we sort the table from max number of black boxes to min number of black box. If the sum concept levels are the same, the concept level with the white block appearing at right is lower. For example, Concept 3 is lower than Concept 4.

Table 5. Several suggestion types of distribution of cognition level and question [20]



Convolutional Neural Network (CNN) to classify the types of the cognition level and question.

Convolutional Neural Network (CNN) imitates the cognition of human brain, for example, CNN identifies an image. It will notice the point, line and surface, and then construct them one by one, for example, eye, and ear. In Fig.1, CNN has convolution layer and pooling layer to make a neural network.

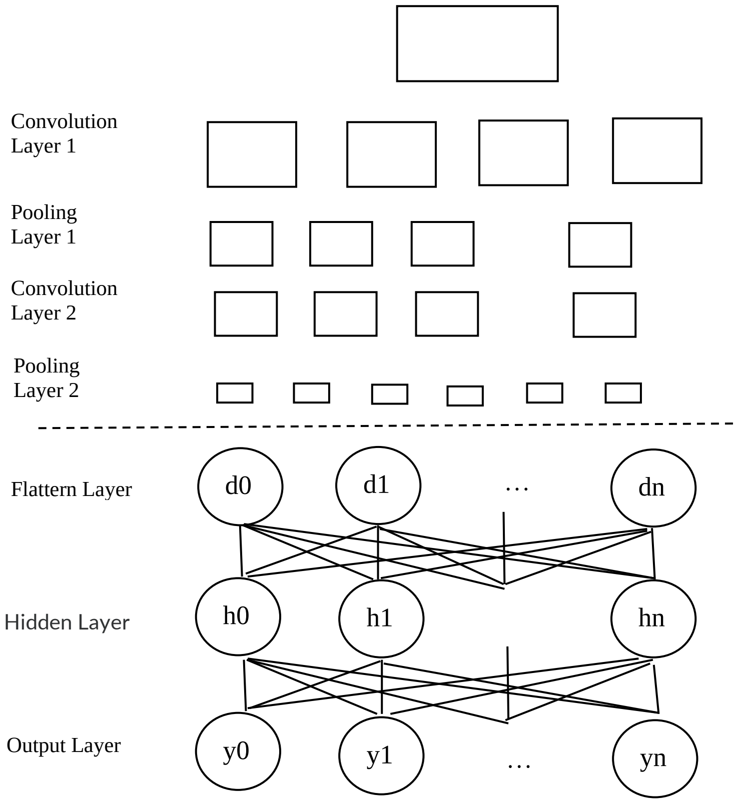


Fig. 1 Convolutional Neural Network (CNN)

The kernel fetches each picture characteristics by the stride movement, which is based on 3*3, 5*5, 7*7 block to move. The movement is from left to right or to the down direction. There are three 3*3 convolution kernel examples in Fig.2.

1	1	1
0	0	0
0	0	0

▲Horizontal

1	0	0
1	0	0
1	0	0

▲Vertical

1	0	0
0	1	0
0	0	1

▲Diagonal

Fig. 2 three 3*3 convolution kernel examples

First of all, the algorithm will calculate the sum after multiplying the corresponding elements from the upper left corner of the original picture. For example, a 5*5 black-white picture, 3*3 convolution kernel, stride movement 1 pixel, and the fetch horizontal characteristic is calculated. The calculation result is listed the following (Fig.3):

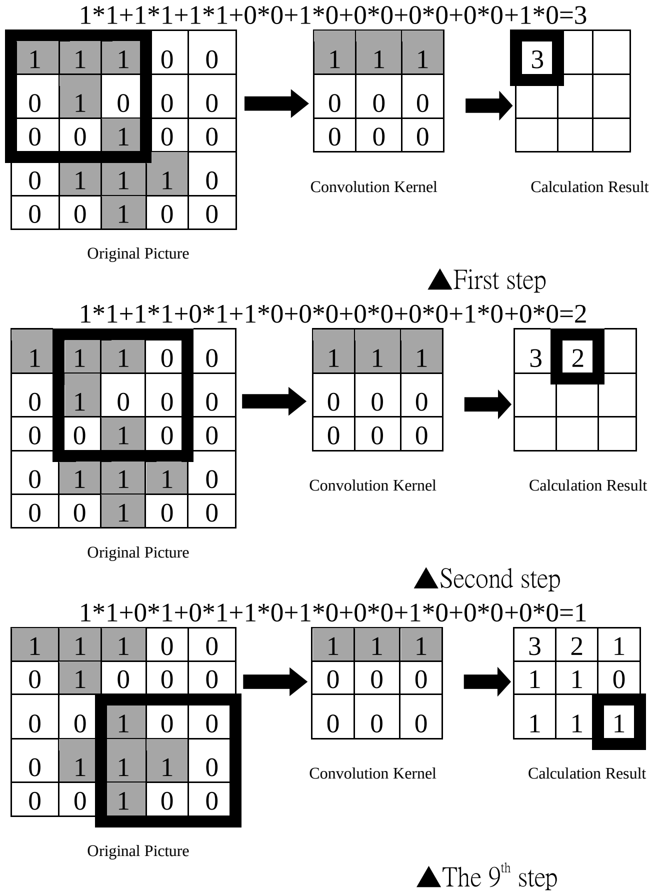


Fig. 3 The procedure from 1st step to 9th step

Picture filling

In some cases, the calculational dimension is 3*3, and the original dimension is 5*5. We hope both dimensions are the same. To solve this problem, we can fill picture with [0] before convolution kernel calculation (see Fig. 4).

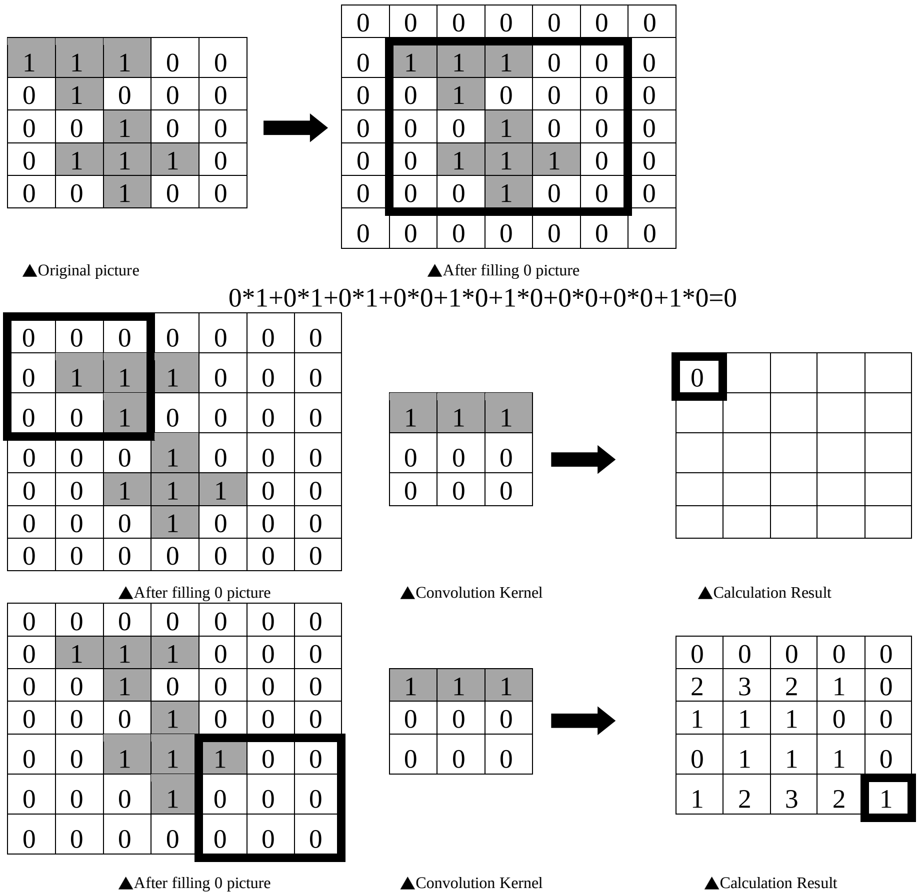


Fig. 4 Picture filling

In the pooling layer, the advantage is reducing the input information, which will not influence the result in most case. To implement the polling layer action, there are two methods, one is “Max Pooling”, and the other is “Average Pooling”. Basically, we select “Max Pooling” to present the most significant feature. The following shows the pooling example (see Fig. 5). The original data is 4*4, and the pooling block is 2*2. After pooling, the result will be 2*2.

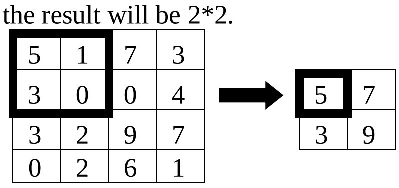


Fig. 5 Max Pooling

Conclusion

Artificial intelligence is composed of machine learning and deep learning. This research using paint algorithm and convolutional neural network to assist teachers to realize the test sheet cognitional level is balanced or not. Owing to the data of the testing sheet are very different. For example, the test sheet of the elementary school will have lower cognition domain, the test sheet will be more appropriate for the elementary students. However, the university course test sheet might have higher cognition domain for university students. Teachers will design the learning material and assessment assets with cognition domain. The cognition distribution and expected teaching for the teachers, it is very critical issue for designing problem-based learning, case-based learning, and other related teaching theories. This work also checks the types of the cognitive level. There are six different types in in the education. We will have a pilot experiment for the algorithm and shows the result soon.

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References

1. Berenguel PO, Guzmán JL, Acién G, Berenguel M, Reul A. An artificial intelligence approach for identification of microalgae cultures.. Authorea Preprints; 2023. DOI: 10.22541/au.167964491.19044370/v1.
2. Chang W.C., Integrating Social Network Analysis with Cooperative Learning in Programming Courses: A Case Study, International Journal of Engineering Education Vol. 39, No. 2, pp. 397–408, 2023
3. Everton Gomede, Rodolfo Miranda de Barros, Leonardo de Souza Mendes, Deep auto encoders to adaptive E-learning recommender system, Computers and Education: Artificial Intelligence, Volume 2, 2021, 100009, ISSN 2666-920X, https://doi.org/10.1016/j.caeai.2021.100009.
4. Joanne Wai Yee Chung, Henry Chi Fuk So, Marcy Ming Tak Choi, Vincent Chun Man Yan, Thomas Kwok Shing Wong, Artificial Intelligence in education: Using heart rate variability (HRV) as a biomarker to assess emotions objectively, Computers and Education: Artificial Intelligence, Volume 2, 2021, 100011, ISSN 2666-920X, https://doi.org/10.1016/j.caeai.2021.100011.
5. Dechawut Wanichsan, Patcharin Panjaburee, Sasithorn Chookaew, Enhancing knowledge integration from multiple experts to guiding personalized learning paths for testing and diagnostic systems, Computers and Education: Artificial Intelligence, Volume 2, 2021, 100013, ISSN 2666-920X, https://doi.org/10.1016/j.caeai.2021.100013.
6. Giuseppina Polito, Marco Temperini, A gamified web based system for computer programming learning, Computers and Education: Artificial Intelligence, Volume 2, 2021, 100029, ISSN 2666-920X, https://doi.org/10.1016/j.caeai.2021.100029.

7. Ke Zhang, Ayse Begum Aslan, AI technologies for education: Recent research & future directions, Computers and Education: Artificial Intelligence, Volume 2, 2021, 100025, ISSN 2666-920X, https://doi.org/10.1016/j.caeai.2021.100025.
8. Venkat Srinivasan, Hemavathi Murthy, Improving reading and comprehension in K-12: Evidence from a large-scale AI technology intervention in India, Computers and Education: Artificial Intelligence, Volume 2, 2021, 100019, ISSN 2666-920X, https://doi.org/10.1016/j.caeai.2021.100019.
9. Chih-Ming Chen, Jung-Ying Wang, Li-Chieh Hsu, An interactive test dashboard with diagnosis and feedback mechanisms to facilitate learning performance,Computers and Education: Artificial Intelligence, Volume 2, 2021, 100015, ISSN 2666-920X, https://doi.org/10.1016/j.caeai.2021.100015.
10. Lu Zheng, Cong Wang, Xue Chen, Yihang Song, Zihan Meng, Ru Zhang, Evolutionary machine learning builds smart education big data platform: Data-driven higher education, Applied Soft Computing, Volume 136, 2023, 110114, ISSN 1568-4946, https://doi.org/10.1016/j.asoc.2023.110114.
11. Muhammad Zahid Iqbal, Abraham G. Campbell, AGILEST approach: Using machine learning agents to facilitate kinesthetic learning in STEM education through real-time touchless hand interaction, Telematics and Informatics Reports, Volume 9, 2023, 100034, ISSN 2772-5030, https://doi.org/10.1016/j.teler.2022.100034.
12. Sarang Shaikh, Sher Muhammad Daudpota, Ali Shariq Imran, Bloom’s Learning Outcomes’ Automatic Classification Using LSTM and Pretrained Word Embeddings August 2021IEEE Access PP(99):1-1, DOI: 10.1109/ACCESS.2021.3106443
13. Yuheng Li, Mladen Rakovic, Boon Xin Poh, Dragan Gasevic, & Guanliang Chen. (2022). Automatic Classification of Learning Objectives Based on Bloom's Taxonomy. Proceedings of the 15th International Conference on Educational Data Mining, 530–537. https://doi.org/10.5281/zenodo.6853191
14. Nazlia Omar, Syahidah Sufi Haris, Rosilah Hassan, Haslina Arshad, Masura Rahmat, Noor Faridatul Ainun Zainal, Rozli Zulkifli,Automated Analysis of Exam Questions According to Bloom's Taxonomy,Procedia - Social and Behavioral Sciences,Volume 59,2012,Pages 297-303,ISSN 1877-0428,https://doi.org/10.1016/j.sbspro.2012.09.278.
15. M. Ifham, K. Banujan, B. T. G. S. Kumara and P. M. A. K. Wijeratne, "Automatic Classification of Questions based on Bloom's Taxonomy using Artificial Neural Network," *2022 International Conference on Decision Aid Sciences and Applications (DASA)*, Chiangrai, Thailand, 2022, pp. 311-315, doi: 10.1109/DASA54658.2022.9765190.
16. Bloom B.S. (1956) Taxonomy of Educational Objectives: The Classfication of Educational Goals: Handbook 1: Cognitive Domain. Longman, New York, Available at: http://www.washington.edu/krumme/guides/bloom.html.
17. Kropp R.P., Stocker H.W. & Bashaw W.L. (1966) The validation of the taxonomy of educational objectives. Journal of Experimental Education 34, 69–76.
18. Seddon M. (1978) The properties of bloom’s taxonomy of educational objectives for the cognitive domain. Review of Educationa Research 48, 303–323
19. Fleishnan E.A. & Quaintance M.K. (1984) Taxonomies of Human Performance: The Description of Human Tasks. Academic/Harcourt Brace Jovanovich, Orlando, FL.
20. Chang, W.C., Hsu, H., Smith, T.K., & Wang, C. (2004). Enhancing SCORM metadata for assessment authoring in e-Learning. *Journal of Computer Assisted Learning, 20*, 305-316.
21. Kelly T.L. (1939) The selection of upper and lower groups for the validation of test items. Journal of Educational Psychology 30, 17–24.