

Application of Convolution Neural Network Algorithm in Online Education Emotion Recognition

Zhaoxing Xu, Jiangxi Institute of Fashion Technology, China*

ABSTRACT

The setting of teaching environment is the key factor of teaching emotion recognition, and its superiority directly determines the teaching and learning effect between teachers and students. During online education, the changes of students' emotions are not paid attention to and addressed by teachers. Especially for young students, their self-study ability and self-discipline are poor, which further affects the learning. This paper proposes an improved convolutional neural network algorithm to create a decision tree model for managing students' scores. The experimental results show that the improved convolutional neural network algorithm improves the construction speed of the decision tree and reduces the calculation and execution time of the algorithm. The improved algorithm proposed in this paper has a good classification effect. The model provides a reference for the expansion and application of emotion recognition big data in education and teaching, and a feasible practical model for personalized teaching in online schools.

KEYWORDS

Big Data, Convolution Neural Network Algorithm, Decision Tree, Level Management, Machine Learning for Secure, Online Teaching System, Privacy-Preserving Mobile

INTRODUCTION

Neural network algorithms will also modernize online education system, allowing learners to get extensive and timely information from multiple channels. The choice of teaching resources will be more diversified and targeted, and learning will be more active and personalized. In addition, the neural network algorithm enables teacher administrators to collect information at low cost comprehensively, compare resources, analyze learners' interests and preferences in real-time, and carry out efficient and targeted online teaching activities (Wagner et al., 2016). The global novel coronavirus epidemic in 2020 makes online education unprecedented prosperity. Students, parents, and teachers from all universities and primary and secondary schools have all invested in online education, recognizing its convenience and irreplaceable nature. Online education makes use of the convenient environment of

DOI: 10.4018/IJWLTT.331077

*Corresponding Author

This article published as an Open Access article distributed under the terms of the Creative Commons Attribution License (<http://creativecommons.org/licenses/by/4.0/>) which permits unrestricted use, distribution, and production in any medium, provided the author of the original work and original publication source are properly credited.

the Internet to enable learners to acquire knowledge anytime and anywhere in a new way, breaking the restrictions of fixed teaching places and fixed teaching time in the traditional teaching process, allowing learners to freely arrange their learning time, flexibly choose learning places, and promoting the development of lifelong learning. Designing and developing emotion recognition in online education and teaching in the big data environment has many practical significances.

Emotional recognition of online physical education is an effective way to stimulate students' interest, motivation, and behavior in physical education and improve teaching effect. Through neural network algorithms to classify massive data, we cannot only obtain the most suitable learning materials for learners, but also get the method of how to learn. Formulate the most appropriate learning plan for efficient learning according to learners' preferences, habits, and rules (Taylor et al., 2017). For many learners, neural network algorithms can also analyze different learning needs according to their needs. After the introduction of mobile technology, the online communication platform of the system can promote customized learning resources and learning methods to learners through the push service of mobile intelligent platforms (Wu & Patel, 2016). The research on grade analysis and evaluation of online classroom systems based on the decisions tree algorithm is based on other libraries' grade bank and student evaluation information (Sosik & Godshalk, 2000).

Emotion is a reaction to certain psychological activities caused by external stimuli, which can affect and adjust cognitive activities such as representation, attention, perception, thinking, memory, and language. The data shows that emotional care is important in improving learners' learning interest and efficiency. To improve the limitations of online education, learning emotion has become a very important breakthrough. In recent years, many scholars have proposed compensation methods for emotional loss. After years of research by scholars, learners' expression recognition in online education provides important feedback for learning emotion analysis. In the research of affective computing technology, learners' emotional information mainly includes voice, facial expressions, physiological signals (such as the speed of heartbeat, sweat, temperature changes, and blood pressure), and posture. Information and communication technology has changed the environment and conditions of college teaching emotion recognition to a great extent. However, from traditional teaching to online teaching and then to mixed learning, teachers need to understand the concept of teaching emotion and then consciously apply and implement it (Cummings et al., 2016). The current university teaching reform provides new ideas and methods, a concept the international education community puts forward after in-depth reflection on the practice of "E-Learning" represented by the United States (Bodyanskiy et al., 2016). There are several advantages of Hybrid Teaching. First, the face-to-face teaching method can alleviate the loneliness and sense of identity that students may encounter in online learning, strengthening the relationship between teachers and students. Second, the use of online teaching methods reduces classroom teaching time, enables students to access more resources they need, and provides greater flexibility (Butz et al., 2003). The traditional classroom model has a fixed time and place, while the mixed classroom can learn anytime, anywhere. In class, 70% of the time is spent on online learning, completing the homework arranged by the teacher on the course platform, and the teacher can also teach the problems that are not understood. Due to the flexibility of learning time, students can improve their autonomous learning ability.

Many existing online learning platforms try to meet the current educational needs and narrow the gap between traditional educational technology and future education. However, the e-learning system developed to achieve this online education goal has lost many functions of education itself, such as personalized education function and tracking learners' emotional feedback function. From previous online teaching activities, we found that online education is a one-way learning process, and there is almost no direct communication between teachers and learners. This one-way learning process leads to the separation of teaching and learning activities and the loss of communication between teachers and learners. Learners will show different expressions to different teaching contents in the teaching process. When learners can accept and clarify the learning content and are interested in it, they will show happy or excited expressions, showing high emotions.

On the contrary, when learners struggle to understand the learning content or do not conform to their interests, they will frown, look bland and dull, and show a low mood. This struggle shows the importance of facial expressions, as they provide essential teaching feedback data for the education platform and educators. The existing online education system is usually centered on the system, which can provide different learning materials and tasks for other students who lack autonomy. Data mining technology can undoubtedly find some potential and valuable rules in the massive data of online education systems, which effectively supports intelligent and personalized online learning (Raza et al., 2016). In this paper, we consider the shortcomings of the existing online learning systems and use the decision tree convolution neural network algorithm to classify learners according to test scores to achieve intelligent learning guidance (Santamaria-Granados et al., 2018). This paper uses a decision tree algorithm to construct a decision tree and form a performance evaluation model. After creating rules, we can analyze and predict the situation of classes according to the attribute information of classes (Ma, 2021). The purpose is to determine the factors that affect students' achievements and relationships, keep students in a good learning state, and provide decision-making support information for academic departments to promote and improve education quality. However, due to some defects in the convolution neural network algorithm, it has been improved based on the original algorithm, and the efficiency and classification accuracy of the improved algorithm has been substantially improved (Na, 2020). Data is vital to big data analysis of convolutional neural network algorithms. In building an online learning system, it is necessary to ensure the comprehensiveness and efficiency of data sources and realize the effective integration of data sources (Dou et al., 2018). Some data in the production system have problems such as nonstandard, incomplete, inaccurate, and inconsistent data, and the collection process does not clean these problems, or the program code for cleaning is incorrect. The data input specifications are not uniform. Different business departments, times, and even when dealing with the same business, the data input specifications differ, resulting in data conflicts or contradictions.

To design the diagnosis algorithm, the first step is to initialize the rule engine; Rule engine has two reasoning methods, the forward chain method and reverse chain method, which correspond to two human ways of thinking: deduction and induction. The core algorithm is the Rete algorithm (Qu, 2021). The rete algorithm is currently effective in a production system. At the same time, it is the only decision- support algorithm, and its efficiency is independent of the number of rules executed. Therefore, it is more suitable for the external language library built in this paper. Drools is an open-source project based on this principle, which uses Java language to implement the inference process of the rules engine (Zheng et al., 2019).

The innovation of this paper is that in the traditional classroom dominated by lectures, teachers' own knowledge structure has been consolidated, and the access to data has also been limited, making it a closed classroom. Similarly, students acquire very limited knowledge in closed classes (Liu, 2017). Neural network algorithm can carry out statistical analysis of massive data through the Internet and build an open classroom, providing learners with massive data resources for use and personalized services. This paper breaks the framework of traditional online education emotion recognition methods, combines neural network algorithm with online education system technology, combines the characteristics of online education resources, learners' characteristics, and behavioral preferences, integrates specific education situations, and forms a closed-loop big data construction environment (Li et al., 2018). The model provides a reference for expanding and applying big data in emotional recognition in education and teaching and a feasible practical model for personalized teaching in online schools.

The rest of the article is structured as follows. First, we introduce the methods and purposes used in the introduction. Second, we outline the development and related research of the decision tree algorithms, and summarize the development work before proposing the traditional decision tree algorithm. The improved convolution neural network algorithm is then analyzed and compared. We then provide the improved convolutional neural network algorithm and the traditional convolutional

neural network algorithm before we compare and analyze them. Finally, we provide an overview and summary of this work.

MATERIALS AND METHODS

With recent technological development and societal progress, China's economy has developed rapidly and made remarkable leaps. As the saying goes, the economic base determines the superstructure, so innovation and improving education are the top priorities in China. We must carry out relevant innovations according to the current situation of relevant education in China, improve the quality of physical education classroom teaching, and help improve the physical quality of young people across the country. Innovation is the only way to carry out related reforms.

Adaptive learning is a systematic study based on computer technology. Of course, it has a series of intuitive and straightforward questions to answer. Mieke Vandewaetere and Geraldine Clarebout define a four-dimensional view (Vandewaetere et al., 2011), namely: What are the changes in the learning process? Why change learning? When did this change happen? How can we make this change in learning (Coşkun et al., 2017)? These four questions are the four dimensions of adaptive learning, the adaptive object, source, time or situation, and method. The answer is different for the learning elements in the learning paradigm. Therefore, in the teaching system, the application of adaptive learning involves the following four aspects: First, the adaptive object, the object of adaptive teaching, can be adjusted to include three aspects. The point is what can be adjusted in the system.

The first is to change the content or title, for example, by differentiating the task or difficulty level of the project. The second is to change the learning content's representation form and path selection, such as hiding or highlighting links (Issa et al., 2020). Then comes the adjustment of teaching levels and available support through indirect guidance, followed by sources of adaptation – learning parameters, learner characteristics, and learning outcomes (Rashid, 2016). More importantly, the time of adaptation, which is the time or context of adaptive learning, when and where adaptation occurs. The last is the adaptation method, which distinguishes between learner-controlled adaptation, system-controlled adaptation, and a combination of the two (Abdullah & Abdulazeez, 2021). System control has many adaptations that are already ubiquitous, while learner control adaptation emphasizes that the learner has complete control over the learning environment and content (Wang et al., 2019). Both adaptive methods have advantages and disadvantages. Shared-control adaptation has been proposed, i.e., selecting a suitable set of learning materials or tasks and considering the learner's characteristics to adapt (Li et al., 2021). The learner is then free to choose materials and tasks.

The Convolutional neural network algorithm has always had drawbacks (Santamaria-Granados et al., 2018). These drawbacks mean that when selecting eigenvalues, it is biased towards problems with more attributes, so the selected features may not be the best choice. Since our problem is related to the selected sample data, there is no control over the sample data, and some data has a certain amount of noise or is sporadic.

RESULTS AND DISCUSSION

Summary of Innovation Education Concept

This paper combines a neural network algorithm with an online education system. Teaching emotion recognition is the extension of quality education. The two complement each other and are interrelated, which is conducive to the teaching concept of cultivating high-quality talents, which is different from the old classroom teaching methods. Teaching emotion recognition is no longer like the old teaching methods, no longer simply teaching students the content of books, but actively guiding students to think, which will help to improve students' thinking ability and practical skills. Table 1 illustrates how high-quality talents play a decisive role (Kamencay et al., 2017).

Table 1. Level table of physical education teaching methods

Teaching Methods	Teaching Methods' Attributes
Organizational pedagogy	To meet the needs of teaching, various forms of teaching grouping (e.g., intra-class grouping, intra-grouping, and individual guidance)
Technical teaching Teaching Practice	Select appropriate teaching methods for technical teaching (e.g., partial solution, segment decomposition, differentiation decomposition) The method of organizing students to practice (e.g., repeated practice, intermittent practice, or circular practice) for the purpose of mastering skills and improving physical fitness.

Theoretical Basis of Improved Algorithms

The core of the convolutional neural network algorithm is to select the best splitting attribute by calculating the information gain. Taking the large attribute as the root node, branches are created according to the different values of the root node, and the same is true for partitioning subsets, which are set by recursively calling the Convolutional neural network algorithm of each subset. Branch nodes of the decision tree until the entire decision tree is generated. It can be seen from the basic principle of the convolutional neural network algorithm that the convolutional neural network algorithm uses the value of each attribute information to determine the division attributes of the data set and tends to favor attributes with more values. A schematic diagram of the decision tree process is shown in Figure 1.

Overcoming Bias in Attribute Selection

New attribute selection criteria can be found based on the basic principles of decision trees. The entropy value of the attribute is chosen as the comparison standard between nodes, as shown in (1).

$$E(A) = \sum_i^V \frac{1}{(p+n)\ln 2} (-p_i \ln \frac{p_i}{p+n_i}) \tag{1}$$

Because $(p+n)\ln 2$ is a constant in the training set, so we can assume that the function $e(A)$ Satisfy formula (2)

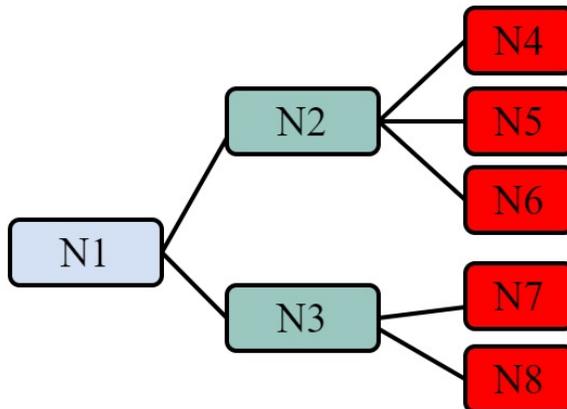


Figure 1. Schematic diagram of the decision tree model

$$e(A) = \sum_i^V -p_i \ln \frac{p_i}{p_i + n_i} \quad (2)$$

Substitute formula (1) into formula (2) to get formula (3)

$$e(A) = \sum_i^V \left(p_i \frac{n_i}{p_i + n_i} + n_i \frac{p_i}{p_i + n_i} \right) \quad (3)$$

The improved solution formula of the attribute information descendant is shown in (4).

$$e(A) = \left(\sum_i^V \frac{2p_i n_i}{p_i + n_i} \right) N \quad (4)$$

Because $e(A)$ It only contains addition, multiplication, and division operations, and the operation time is shorter than $E(A)$ The computation time is shorter for multiple logarithmic terms.

EXPERIMENTAL ANALYSIS

Improved Algorithm Verification

The Convolutional neural network algorithm has always had its drawbacks. The drawbacks mean that when selecting eigenvalues, it is biased towards problems with more attributes, so the selected features may not be the best choice. Since this problem is related to the selected sample data, there is no control over the sample data, and some data has a certain amount of noise or is sporadic. A prediction model can be trained to correct the error between input and output variables to reduce noise impact. The feature information gain value is adjusted by removing the weight of prior knowledge when calculating the information gain to achieve the ability to correct some wrong branches. In this section, we choose the test score as the root node, adopt the improved convolution network algorithm, and select the internal nodes' characteristics to conduct class management and teacher assignments. The convolution network algorithm flow is shown in Figure 2.

Data Pre-Processing

Data collection is an integral part of a decision tree system and is the first link in a decision tree. This paper adopts the dimensionality reduction method. In other words, it is a way to find really useful attributes among the attributes of the initial attributes and reduce the number of attributes, or attribute variables, to consider in a decision tree. This paper selects the attributes of subject types (A, B, C, or D) that are highly correlated with grades and selects test difficulty (high, medium, or low), test delivery time (normal or short), test scores (excellent, good, or poor) to create a base data table to categorize how good or bad the scores are. The training set of student test scores is shown in Table 2.

$$\text{When } t1=A \text{ Yes, } p1=2, n1=2, \text{ Available: } e(t1) = \sum_1^N \frac{1}{(p+n) \ln 2} - p_1 \ln \frac{2p_1 n_1}{p_1 + n_1} = 2.2$$

$$\text{When } t2=B \text{ Yes, } p2=1, n2=2, \text{ Available: } e(t2) = \sum_2^N \frac{1}{(p+n) \ln 2} - p_3 \ln \frac{2p_2 n_2}{p_2 + n_2} = 1.666$$

Figure 2. Convolution network algorithm flow

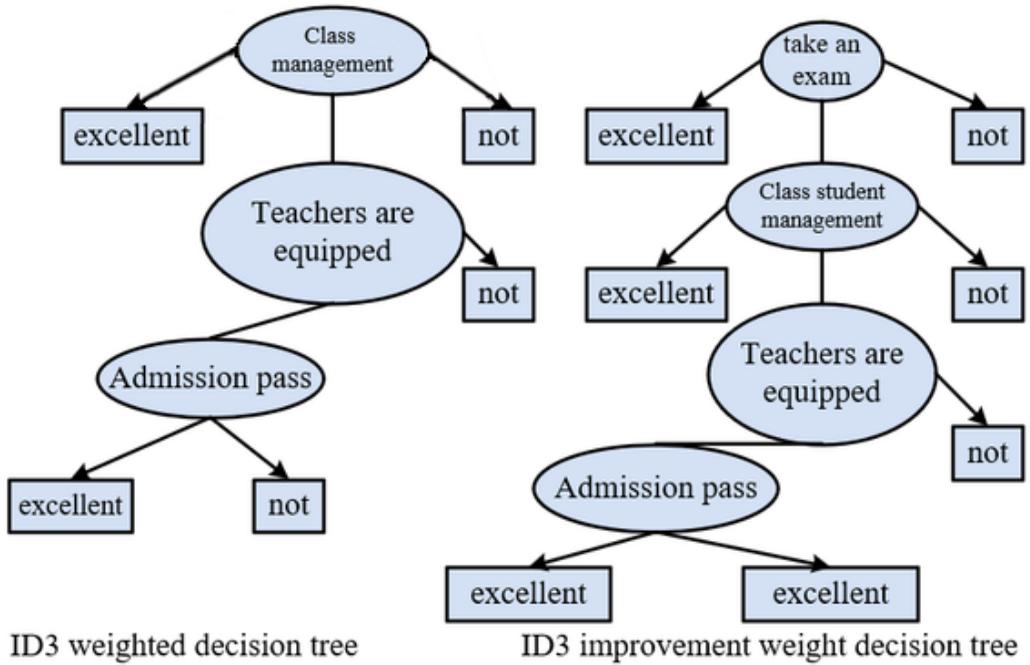


Table 2. Training set of student test scores

Student ID	Course Type	Exam Difficulty	Turnover Time	Test Scores	Overall Review
1	C	middle	normal	excellent	YES
2	A	high	short	good	YES
3	A	Low	normal	Difference	YES
4	B	middle	normal	excellent	NO
5	B	Low	normal	Difference	YES
6	C	middle	normal	good	YES
7	D	high	normal	excellent	YES
8	B	middle	normal	excellent	NO
9	C	middle	normal	good	YES
10	D	high	short	good	YES

When $t_3=C$ Yes, $p_3=3$, $n_3=2$, Available: $e(t_3) = \sum_3 \frac{1}{(p+n)\ln 2} - p_3 \ln \frac{2p_3 n_3}{p_3 + n_3} = 2.512$

When $t_4=D$ when, $p_4=2$, $n_4=2$, Available: $e(t_4) = \sum_4 \frac{1}{(p+n)\ln 2} - p_4 \ln \frac{2p_4 n_4}{p_4 + n_4} = 1.387$

Select the handover time as the test attribute, and the information entropy of the handover time can be obtained after the calculation is 15.2714. Select the test score as the test attribute, and the information entropy of the test score is 5.3287. Justify analyzing the information on test scores that is most helpful for classification.

Classification Performance Analysis

This section uses the existing Convolutional neural network algorithm and the improved Convolutional neural network algorithm for testing, and four data sets are compared. Furthermore, the above experimental data analysis compares and analyzes the differences between the Convolutional neural network algorithm and the improved Convolutional neural network algorithm in the above four aspects. Dset1: There are 874 instances in total, five condition attributes and one category attribute, one condition attribute is continuous, and the category attribute has three different values.

Dset2: There are 968 instances, six condition attributes, and one category attribute . 1 condition attribute is continuous, and the category attribute has 3 different values.

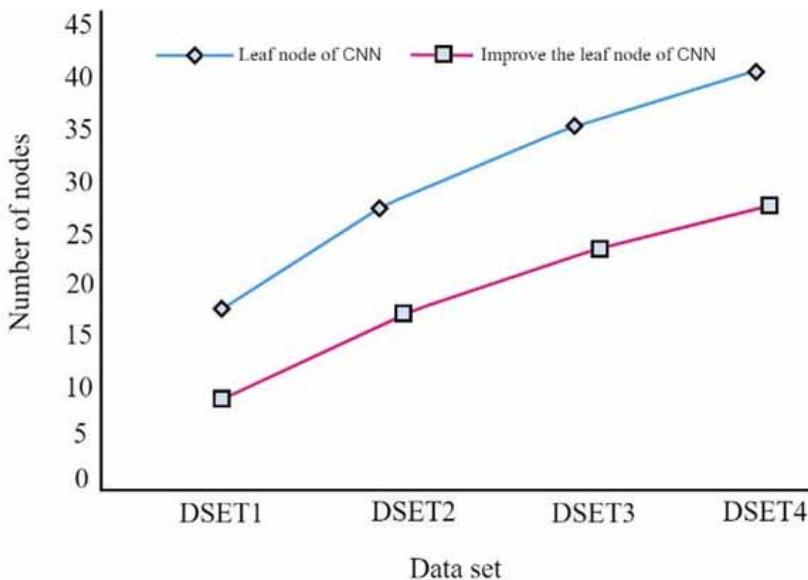
Dset3: There are 1282 instances, 7 conditional attributes and one category attribute, 1 conditional attribute is a continuous attribute, and the category attribute has 3 different values.

Dset4: There are 1548 instances in total, 24 conditional attributes, and one category attribute, 3 conditional attributes are continuous attributes, and the category attribute has 3 different values. The comparison results are shown in Table 3 and Figure 3. shown.

Table 3. Comparison of the number of nodes

Data Set	Record Quantity	Leaf Node of CNN	Improve the Leaf Node of CNN
Dset1	874	15	7
Dset2	968	26	16
Dset3	1282	36	22
Dset4	1548	43	28

Figure 3. Comparison of the number of nodes



It can be seen from the example in Figure 3 that the scale of the decision tree constructed by the improved algorithm is much smaller than that constructed by CNN. The larger the instance set and the more attribute sets, the more pronounced this advantage is. A comparison of the number of rules is shown in Table 4 and Figure 4.

It can be seen from Figure 4 that the number of decision tree rules composed of the improved algorithm is much smaller than the number of decision tree rules composed of CNN. The number of rules corresponds to the number of leaf nodes. The fewer leaf nodes, the fewer the number of rules. The larger the instance set, the more attribute sets, the more noticeable these advantages are. The accuracy comparison is shown in Table 5 and Figure 5.

Table 4. Comparison of numbers of rules

Data Set	Number of Records	Number of Rules for CNN	Improve the Number of Rules for CNN
Dset1	874	55	44
Dset2	968	85	68
Dset3	1282	104	84
Dset4	1548	124	102

Figure 4. Comparison of number of rules

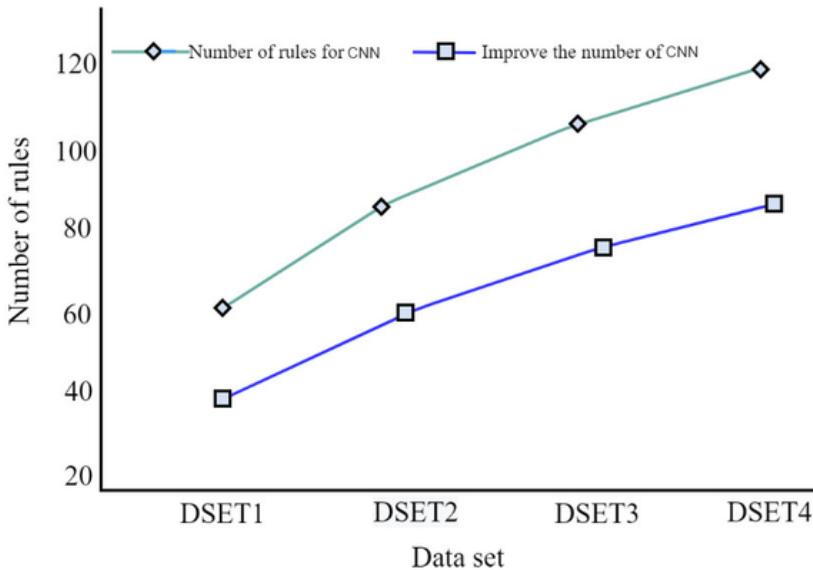
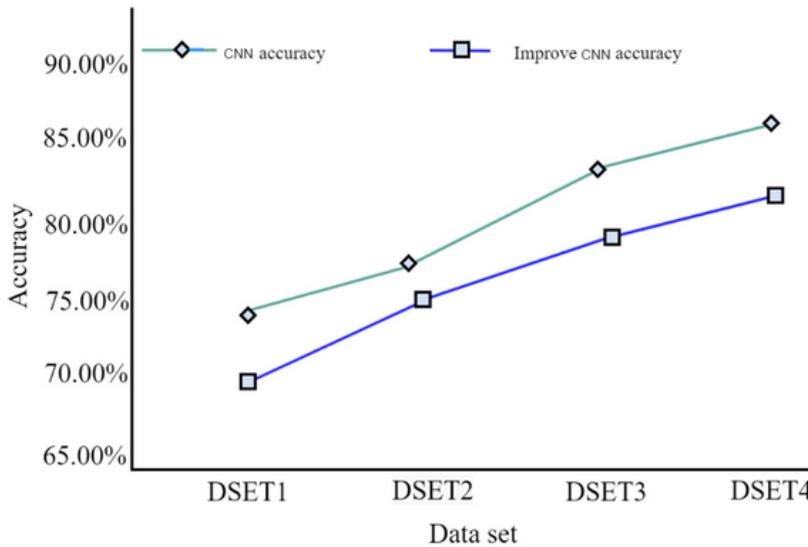


Table 5. Comparison of accuracy rates

Data Set	Number of Records	CNN Accuracy	Improve CNN Accuracy
Dset1	874	67.7%	73.5%
Dset2	968	72.6%	75.7%
Dset3	1282	80.5%	84.3%
Dset4	1548	85.3%	88.5%

Figure 5. Accuracy comparison



It can be seen from the figure that the improved Convolutional neural network algorithm is more accurate than the existing Convolutional neural network algorithm. Moreover, as the amount of data increases, the time difference increases linearly, and the comparison of the time to build the decision tree is shown in Table 6 and Figure 6.

It can be seen from the figure that the improved Convolutional neural network algorithm takes less time than the existing Convolutional neural network algorithm, which fully shows that the improved Convolutional neural network algorithm has greater efficiency and efficiency than the original Convolutional neural network algorithm in the decision tree construction process of larger data sets, giving a performance advantage.

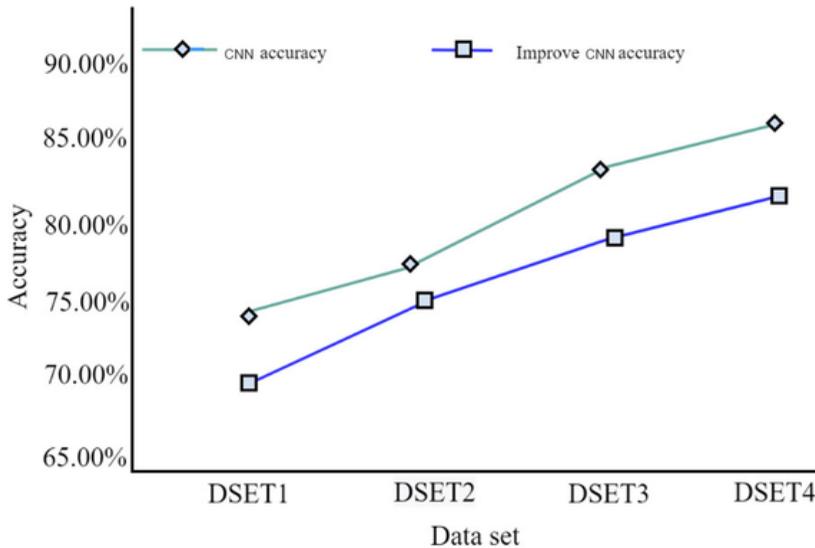
CONCLUSION

With the rapid development of computer and Internet technology, teaching emotion recognition can be developed and promoted. Teaching emotion recognition emphasizes the combination of traditional learning and the Internet and improves teaching effectiveness. On the other hand, adaptive learning is a new education mode based on computer technology. The application of the improved convolution neural network algorithm in the adaptive online physical education teaching system in the big data environment is to comprehensively analyze and evaluate students according to the score database

Table 6. Comparison of time to build a decision tree

Data Set	Number of Records	Average Time Spent by CNN (s)	Average Time (s) Taken to Improve CNN
Dset1	874	153.9	124.7
Dset2	968	252.6	200.5
Dset3	1282	351.4	261.1
Dset4	1548	420.3	308.5

Figure 6. Comparison of the time to build a decision tree



information and the student evaluation information of other databases. The decision tree algorithm builds a decision tree and forms a performance evaluation model. After creating rules, we can analyze and predict the class's situation according to the class's emotional recognition attribute information. The purpose is to determine the factors that affect students' performance and relationship, so that students can maintain a good learning state and provide decision-support information and education quality for academic departments to promote and improve teaching. The designed learning model is applied to evaluating sports performance and compared with the manual test of physical education teachers. By testing individuals and the whole class, it is concluded that the difference between the test data and the actual data is within an acceptable range. This paper verifies the effectiveness of the proposed algorithm and shows that the adaptive learning model can provide new ideas for college students' physical education learning.

We have not considered the mechanism of the emotional bond between teachers and students in the online physical education system. This rich area is the work of the future.

AUTHOR'S NOTE

The article includes the figures and tables used to support this study's findings.

The authors declare that they have no conflicts of interest.

The authors sincerely thank those whose techniques have contributed to this research.

This work was supported by the Research Project on Teaching Reform of Higher Education Institutions in Jiangxi Province: "Research and Practice on the Training Mode of Applied Talents for Software Engineering Majors in Garment Colleges Driven by Digital Economy"(Project No: JXJG-22-26-4)

REFERENCES

- Abdullah, S. M. S., & Abdulazeez, A. M. (2021). Facial expression recognition based on deep learning convolution neural network: A review. *Journal of Soft Computing and Data Mining*, 2(1), 53–65.
- Bodyanskiy, Y. V., Tyshchenko, O. K., & Kopaliani, D. S. (2016). Adaptive learning of an evolving cascade neo-fuzzy system in data stream mining tasks. *Evolving Systems*, 7(2), 107–116. doi:10.1007/s12530-016-9149-5
- Butz, M. V., Sigaud, O., & Gerard, P. (2003). Internal models and anticipations in adaptive learning systems. In M. V. Butz, O. Sigaud, & P. Gérard (Eds.), *Anticipatory behavior in adaptive learning systems: Foundations, theories, and systems* (pp. 86–109). Springer. doi:10.1007/978-3-540-45002-3_6
- Coşkun, M., Uçar, A., Yildirim, Ö., & Demir, Y. (2017, November). Face recognition based on convolutional neural network. *2017 International Conference on Modern Electrical and Energy Systems (MEES)*, 376-379. doi:10.1109/MEES.2017.8248937
- Cummings, R., Ligett, K., Nissim, K., Roth, A., & Wu, Z. S. (2016). Adaptive learning with robust generalization guarantees. *Conference on Learning Theory*, 772-814.
- Dou, Y., Fei, X., Zhu, R., Gao, T., Wu, Y., & Ma, L. (2018). Application of improved ECLAT algorithm in students' evaluation of teaching. *MATEC Web of Conferences*, 228, 01017.
- Issa, D., Demirci, M. F., & Yazici, A. (2020). Speech emotion recognition with deep convolutional neural networks. *Biomedical Signal Processing and Control*, 59, 101894. doi:10.1016/j.bspc.2020.101894
- Kamencay, P., Benco, M., Mizdos, T., & Radil, R. (2017). A new method for face recognition using convolutional neural network. *Advances in Electrical and Electronic Engineering*, 15(4), 663–672. doi:10.15598/aeec.v15i4.2389
- Li, Q., Liu, Y. Q., Peng, Y. Q., Liu, C., Shi, J., Yan, F., & Zhang, Q. (2021). Real-time facial emotion recognition using lightweight convolution neural network. *Journal of Physics: Conference Series*, 1827(1), 012130. doi:10.1088/1742-6596/1827/1/012130
- Li, Y., Wang, G., Nie, L., Wang, Q., & Tan, W. (2018). Distance metric optimization driven convolutional neural network for age invariant face recognition. *Pattern Recognition*, 75, 51–62. doi:10.1016/j.patcog.2017.10.015
- Liu, X. (2017). The application of data mining technology in the teaching evaluation in colleges and universities. *Journal of Computational and Theoretical Nanoscience*, 14(1), 7–12. doi:10.1166/jctn.2017.6115
- Ma, J. (2021). Intelligent decision system of higher educational resource data under artificial intelligence technology. *International Journal of Emerging Technologies in Learning*, 15(5), 6–7. doi:10.3991/ijet.v16i05.20305
- Na, G. (2020). Research on remote control method of English multimedia online teaching system in big data environment. *Journal of Physics: Conference Series*, 1486(5), 052010. doi:10.1088/1742-6596/1486/5/052010
- Qu, J. (2021). Research on mobile learning in a teaching information service system based on a big data driven environment. *Education and Information Technologies*, 26(5), 6183–6201. doi:10.1007/s10639-021-10614-z
- Rashid, T. A. (2016). Convolutional neural networks-based method for improving facial expression recognition. *The International Symposium on Intelligent Systems Technologies and Applications*, 73-84. doi:10.1007/978-3-319-47952-1_6
- Raza, H., Cecotti, H., Li, Y., & Prasad, G. (2016). Adaptive learning with covariate shift-detection for motor imagery-based brain-computer interface. *Soft Computing*, 20(8), 3085–3096. doi:10.1007/s00500-015-1937-5
- Santamaria-Granados, L., Munoz-Organero, M., Ramirez-Gonzalez, G., Abdulhay, E., & Arunkumar, N. J. I. A. (2018). Using deep convolutional neural network for emotion detection on a physiological signals dataset (AMIGOS). *IEEE Access : Practical Innovations, Open Solutions*, 7, 57–67. doi:10.1109/ACCESS.2018.2883213
- Santamaria-Granados, L., Munoz-Organero, M., Ramirez-Gonzalez, G., Abdulhay, E., & Arunkumar, N. J. I. A. (2018). Using deep convolutional neural network for emotion detection on a physiological signals dataset (AMIGOS). *IEEE Access : Practical Innovations, Open Solutions*, 7, 57–67. doi:10.1109/ACCESS.2018.2883213

- Sosik, J. J., & Godshalk, V. M. (2000). Leadership styles, mentoring functions received, and job-related stress: A conceptual model and preliminary study. *Journal of Organizational Behavior*, 21(4), 365–390. doi:10.1002/(SICI)1099-1379(200006)21:4<365::AID-JOB14>3.0.CO;2-H
- Taylor, B., Francis, B., Archer, L., Hodgen, J., Pepper, D., Tereshchenko, A., & Travers, M. C. (2017). Factors deterring schools from mixed attainment teaching practice. *Pedagogy, Culture & Society*, 25(3), 327–345. doi:10.1080/14681366.2016.1256908
- Vandewaetere, M., Desmet, P., & Clarebout, G. (2011). The contribution of learner characteristics in the development of computer-based adaptive learning environments. *Computers in Human Behavior*, 27(1), 118–130. doi:10.1016/j.chb.2010.07.038
- Wagner, N., Rieger, M., & Voorvelt, K. (2016). Gender, ethnicity and teaching evaluations: Evidence from mixed teaching teams. *Economics of Education Review*, 54, 79–94. doi:10.1016/j.econedurev.2016.06.004
- Wang, Y., Li, Y., Song, Y., & Rong, X. (2019). The application of a hybrid transfer algorithm based on a convolutional neural network model and an improved convolution restricted Boltzmann machine model in facial expression recognition. *IEEE Access : Practical Innovations, Open Solutions*, 7, 184599–184610. doi:10.1109/ACCESS.2019.2961161
- Wu, E., & Patel, S. (2016). Teaching mixed methods research through blended learning: Implications from a case in Hong Kong. *Journal of Educational Enquiry*, 15(1), 15–U47.
- Zhang, W. (2020). Research on English score analysis system based on improved decision tree algorithm and fuzzy set. *Journal of Intelligent & Fuzzy Systems*, 39(4), 5673–5685. doi:10.3233/JIFS-189046
- Zheng, S. Y., Jiang, S. P., Yue, X. G., Pu, R., & Li, B. Q. (2019). Application research of an innovative online education model in big data environment. *International Journal of Emerging Technologies in Learning*, 14(8), 125. doi:10.3991/ijet.v14i08.10404