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RESEARCH ARTICLE

Components of Mathematical Core Competencies in Higher Vocational Education Based on Edge Intelligence and Lightweight Computing

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ABSTRACT

In view of the low level of personalized teaching and the low level of core competency components in higher vocational mathematics, this article conducts research on the core competency components of higher vocational mathematics in combination with edge computing and lightweight computing. Firstly, mathematical learning-related data is collected from a certain higher vocational college, and image clarity and normalization processing are performed on the data. Then, the MobileNet-V2 (Mobile Network Version 2) model is used to extract features from electronic images of students' math papers, and the extracted image features are combined with mathematical core competencies. A feature representation is constructed and the evaluation results of the mathematical core competency level of vocational college students are output. Finally, based on the evaluation results of the mathematical core competency level of vocational college students, an item-based collaborative filtering (IBCF) algorithm is applied to provide personalized course recommendations for their mathematical core competency. An evaluation system is developed for mathematical core competencies based on the constructed summation model. The experimental results shows that the accuracy of the core competency level evaluation of the experimental model reaches 92.32%; the recommendation accuracy reaches 95.31%; the degree of diversification reaches 88.77%. Combining edge computing and lightweight technology to evaluate and recommend the core competencies of higher vocational students improves the level of students' mathematical core competencies and the degree of personalization, promotes the development process of higher vocational education, and has good adaptability to the resource-constrained edge environment

INTRODUCTION

In recent years, higher vocational mathematics education has faced many challenges in response to the increasing diversity and complexity of vocational education (Mutohhari et al., 2021; McGrath et al., 2022). Traditional teaching methods often fail to meet the personalized learning needs of students, and the level of core competency components also urgently needs to be improved. With the advancement of technology and the development of society, there is an urgent need for a new education model to address these challenges. This article aims to explore innovative paths in higher vocational mathematics education through the use of edge intelligence and lightweight computing technology, in order to improve students' core competency level and promote the comprehensive development of their application abilities.

With the increasing application of mathematics in important fields such as national engineering and manufacturing, many scholars have conducted research on the cultivation of core competencies in vocational mathematics education, achieving a large number of research results and improving teaching and education methods. The application of the Internet in mathematics education environment is gradually widespread, and the application of digital technology has an important impact on the different ways of cultivating students' new thinking mode in mathematics teaching and learning environment (Engelbrecht et al., 2020). Irfan M and other scholars used online learning platforms to implement personalized teaching plans in higher education mathematics learning, and the results showed that they met the needs of the actual environment, but the teaching efficiency was not ideal (Irfan et al., 2020; Kara, 2022). In order to enhance students' mathematical core competencies, scholars such as Cevikbas M conducted experiments on higher vocational students using the flipped classroom teaching method, which improved their mathematical thinking and understanding of mathematical knowledge (Cevikbas and Kaiser, 2020). Mathematical core competencies cover multiple aspects, including mathematical abstraction (Fatımah and Prabawanto, 2020), logical reasoning (Hidayat et al., 2022), mathematical modeling (Kutluca and Kaya, 2023), intuitive imagination (Wei et al., 2023), mathematical operations and data analysis (Brezavšček et al., 2020; Chairil et al., 2020), and is gradually being studied. These qualities can enrich students' mathematical thinking abilities and enhance their overall competency level. The research of the above scholars has shown good improvement in various aspects of the components of students' mathematical core competencies, but there is still a significant gap in personalized education.

In recent years, edge intelligence and lightweight computing have gradually become hot topics, and many scholars have begun to explore new methods suitable for higher vocational mathematics education. Mendez et al. (2022) and Jiao (2021) developed an English teaching information service platform using edge intelligence technology, further improving teaching efficiency and achieving personalized teaching. To address the issue of energy distribution, Sayed et al. (2021) and Meng et al. (2021) applied edge intelligence technology to personalized energy transmission, improving the degree of personalization in energy allocation recommendations. Al-Rakhami et al. (2020) introduced the application of lightweight, cost-effective edge intelligence architecture based on containerization technology, providing a solid foundation for the research on the components of mathematical core competencies in higher vocational education. Lightweight computing ensures data processing and decision-making efficiency in resource-constrained Internet of Things (IoT) devices (Bandara et al., 2021; Haque et al., 2024). It can be found that the application of edge intelligence and lightweight computing to studying the components of mathematical core competencies in higher vocational education is feasible. Although the research of the above scholars is helpful for the degree of personalization in higher vocational mathematics, there is still room for improvement.

Article contribution:

(1) In order to solve the problem of low personalized teaching level and low level of core competency components in higher vocational mathematics, this article combines the MobileNet-V2 model and item-based collaborative filtering algorithm to evaluate students' mathematical core competency level and recommend personalized courses.

(2) The experiment fully considers the edge environment with limited resources, ensuring high evaluation and recommendation performance in such environments, and improving students' mathematical core competency level.

(3) This article achieves superior prediction performance by processing the math score and answer

data of a certain higher vocational school. The experimental method achieves good performance in evaluation accuracy and degree of personalization, and the level of mathematical core competency after learning the recommended course is not lower than that before learning the recommended course.

Components and Applications of Mathematical Core Competencies in Higher Vocational Education

2.1 Components of Mathematical Core Competencies in Higher Vocational Education

In higher vocational education, mathematical core competencies require students to possess basic mathematical qualities and abilities, enabling them to effectively apply mathematical knowledge to solve practical problems and adapt to the needs of career development for mathematical skills and thinking methods (Nasrulloh et al., 2023; Yang et al., 2020). The mathematical core competencies cover the following aspects, as shown in Figure 1.

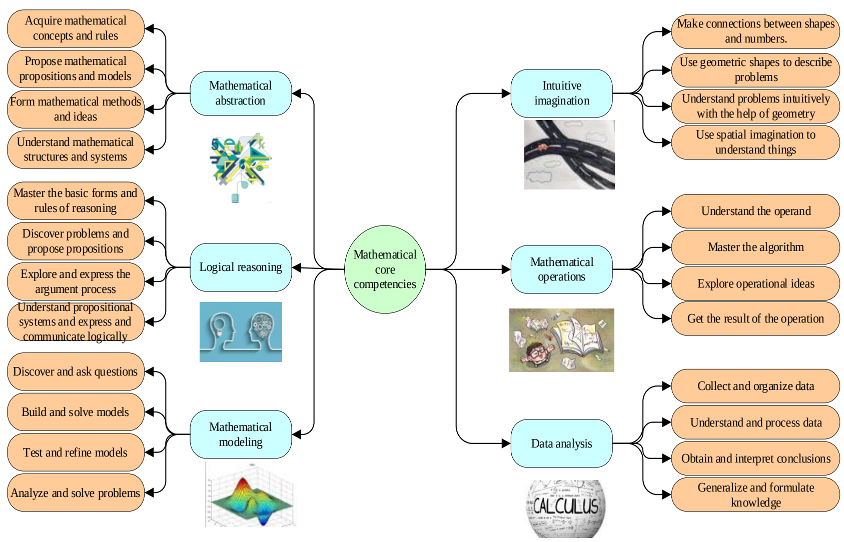


Figure 1. Components of mathematical core competencies

In Figure 1, it can be seen that the components of mathematical core competencies include six aspects: mathematical abstraction, logical reasoning, mathematical modeling, intuitive imagination, mathematical operations, and data analysis. The cultivation of mathematical core competency components is an important goal of higher vocational mathematics education.

2.2 Role of Mathematical Core Competencies in Higher Vocational Education

The mathematical core competencies play an important role in higher vocational education, and its roles are as follows:

(1) In mathematics teaching, the main approach is to cultivate students' mathematical core competencies, which can help them establish a solid mathematical foundation, improve their ability to solve practical vocational problems, and thus enhance their vocational skills.

(2) Mathematical core competencies help cultivate students' critical thinking, innovative thinking, and problem-solving abilities, enabling them to apply mathematical knowledge to analyze and solve practical problems.

(3) Mathematics has strong logic. Cultivating students' mathematical core competencies can enhance their logical thinking ability, improve their ability to analyze problems and make decisions, and lay a

solid foundation for their future career.

(4) If students have good mathematical core competencies, they can become more competitive in their career development in different fields. In fields such as scientific research, engineering technology, financial investment, and data analysis, mathematical knowledge is needed to solve problems.

(5) Mathematical core competencies helps to cultivate students' learning and self-development abilities, enabling them to continuously learn and adapt to the needs of career development, and achieve the goal of lifelong learning.

Edge Intelligence Technology

Edge intelligence refers to pushing intelligent computing and processing capabilities to the edge of a network, enabling faster and more real-time data analysis and decision-making (Deng et al., 2020; Jiang et al., 2021). Edge intelligence deploys data processing and analysis functions to local devices such as devices, sensors, or edge servers, reducing the need for data transmission to the cloud and thereby reducing latency and improving system response speed, which can help to address network congestion and latency issues caused by large-scale data transmission and processing.

Edge intelligence technology combines edge and intelligence, in which edge intelligence deploys artificial intelligence services through edge computing and outputs edge-intelligence technology. Edge intelligence technology integrates artificial intelligence technology into edge computing networks, creates dynamic and adaptive edge network management and maintenance, and outputs intelligence-edge technology (Zheng et al., 2023). Edge-intelligence is the goal of edge intelligence, which pushes deep learning computing from the cloud to the edge, ensuring the diversity, distribution, low latency, and reliability of intelligent services. From the perspective of intelligence-edge, deep learning services, as a part of edge intelligence, manage and maintain the architecture of terminal edge cloud through deep learning, and output higher service throughput and resource utilization for edge intelligence. The edge intelligence architecture is shown in Figure 2.

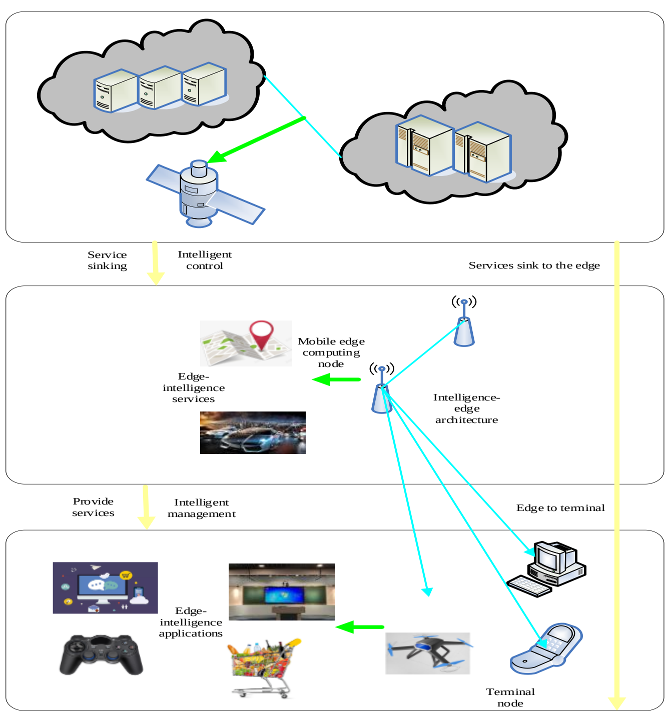


Figure 2. Edge intelligence architecture

In Figure 2, as a whole, from the top cloud layer to the edge terminal layer, the terminal node layer includes terminal nodes, edge-intelligence applications, and intelligent applications provide services in mathematical intelligent education and personalized recommendation. The edge layer mainly consists of edge-intelligence services and intelligence-edge architecture, providing services and management for the terminal layer. The cloud layer provides service sinking and intelligent control services for the lower layer, and gradually sink the services to the edge.

Lightweight Computing Model MobileNet and Collaborative Filtering Algorithm

4.1 MobileNet Model

In resource-limited deployment environments such as edge devices, in order to achieve lightweight computing while ensuring model performance, the design is optimized to greatly reduce the number of model parameters and further reduce the complexity of experimental operation.

MobileNet (Mobile Network) is a lightweight deep neural network architecture designed to achieve efficient tasks on mobile devices with limited computing resources (Bouguezzi et al., 2021; Zhao and Wang, 2022). In MobileNet, depthwise separable convolution and layer-by-layer channel reduction methods are used (Nguyen, 2020). Depthwise separable convolution is a method of decomposing standard convolution operations into depthwise convolution and point-by-point convolution to reduce the number of parameters and computational complexity. A network with adjustable width can adjust the number of channels at different levels of the network, thereby achieving different model sizes and performance under different resource constraints.

4.2 Parameter Pruning

In edge devices, computing power and storage space are relatively limited, and lightweight optimization design is being carried out in the experiment. Parameter pruning, with known weight sizes, defines small weights below a specific threshold as 0 and outputs the compressed model. The expression of parameter pruning is shown in Formula (1).

$$\hat{V}_{jk} = \begin{cases} V_{jk} & if|V_{jk}| > \alpha \\ 0 & otherwise \end{cases} \tag{1}$$

In Formula (1), α represents a specific threshold. The corresponding elements of the weight matrix before pruning are represented by V_{jk}, and the corresponding elements of the weight matrix after pruning are represented by $\hat{V}_{jk}$.

4.3 Large Model Simulated by Small Model

To achieve better learning outcomes, the designed objective function is shown in Formula (2).

$$M_{NE} = \sum_{j=1}^{L} \beta(x_j, \tilde{x}_j) + (1-\beta)G(q_j, \tilde{q}_j) \tag{2}$$

In Formula (2), the balance function is represented by β. x and $\tilde{x}$ represent real labels. q and $\tilde{q}$ represent the corresponding output.

In the network model, the model weights and activated bit points are defined to be reduced, as shown in Formula (3).

$$\mathrm{y} = \frac{\mathrm{round}(\mathrm{y}/\gamma)}{\gamma} \times \gamma \tag{3}$$

In Formula (3), γ represents the scaling factor, and y represents the original value corresponding to the floating-point weight.

4.4 Fixed-point Operations

In floating-point operations, it is difficult to adapt to edge environments, especially on embedded platforms for mathematics education. Fixed-point operations can greatly improve computational efficiency, and there is a lot of space in chip area. The specific representation of fixed base points is shown in Formula (4).

$$y = y_e \cdot 2^y \tag{4}$$

In Formula (4), y_e corresponds to the decimal part.

The definitions of integer and decimal places are shown in Formulas (5) and (6).

$$Q_z = log_2(max|y|) \tag{5}$$

$$Q_x = -log_2(min|y|) \tag{6}$$

Among them, y represents the input of the corresponding layer.

The experiment aims to quantify the error, and now the activation function is quantized as shown in Formula (7).

$$q(y) = round(y \cdot 2^{Q_x}) \cdot 2^{-Q_x} \tag{7}$$

4.5 Storage Optimization

In terms of storage optimization, this experiment adopts the operation of reducing parameter redundancy and data width. In parameter redundancy, it is mainly achieved by decomposing the weight matrix, which can greatly reduce the number of parameters, reduce storage requirements, and make it more adaptable in edge first environments.

In terms of data width, this experiment uses vectorization optimization to parameterize the index corresponding to the vectors in the codebook. The calculation formula is shown in Formula (8).

$$\hat{v} = {}^{argmin}_{d_{j \epsilon D}} ||v - d_j||_2 \tag{8}$$

In Formula (8), the vector code is represented by D.

4.6 MobileNet-V2 Model

Based on the above design, the MobileNet-V2 model is selected for training in this experiment. In MobileNet-V2, it is composed of modules such as depthwise separable convolution and residual connections (Srivastava et al., 2020). The calculation formula for the depthwise separable convolution operation of a certain layer in the MobileNet-V2 model is shown in Formula (9).

$$Z_i = \rho(U_{1,i} * \rho(U_{0,i} * Y_i)) \tag{9}$$

In Formula (9), Z_i represents the feature map of the model input. ρ represents the activation function. $U_{0,i}$ represents a channel wise convolution kernel, and $U_{1,i}$ corresponds to a point wise convolution kernel.

The residual block can effectively avoid the problem of gradient vanishing during the training process, and the calculation formula is shown in Formula (10).

$$Z_i = Y_i + H(Y_i, U_i) \tag{10}$$

In Formula (10), the residual function is represented by H.

The calculation formula for the overall MobileNet-V2 is shown in Formula (11).

$$Z = g(Y, U) = (\ldots(g_1(g_0(Y, U_0), U_1)\ldots) + Y) \tag{11}$$

In Formula (11), both g_0 and g_1 represent different layer operations of the network.

4.7 Collaborative Filtering Algorithm

In this experiment, based on the evaluation results of students' mathematical core competencies, an item-based collaborative filtering algorithm (Ajaegbu, 2021; Tewari, 2020) is applied to personalized recommendation. The item-based collaborative filtering algorithm is a recommendation system algorithm used to predict the user's preference for items not evaluated, based on the similarity between items for recommendation. If a user likes an item, other similar items can be recommended to that user.

In terms of similarity calculation between items, this article uses Pearson correlation coefficient for calculation, and the specific formula is shown in Formula (12).

$$\mathrm{sim}(b_1, b_2) = \frac{\sum_1^N (Q_{1,m} - \bar{Q}_1) \times \sum_1^N (Q_{2,m} - \bar{Q}_2)}{\sqrt{\sum_1^N (Q_{1,m} - \bar{Q}_1)^2} \times \sqrt{\sum_1^N (Q_{2,m} - \bar{Q}_2)^2}} \tag{12}$$

In Formula (12), $Q_{1,m}$ represents the potential rating of Student 1's mathematical core competencies on the training course, and N represents the training course corresponding to the joint evaluation of Student 1's mathematical core competencies and Student 2's mathematical core competencies.

Experiment on Mathematics Core Competencies and Personalized Evaluation of Higher Vocational Students

5.1 Experimental Environment

Hardware device: server model Dell PowerEdge R740, NVIDIA Tesla V100 GPU (Graphics Processing Unit) accelerator card, 192GB of memory.

Software environment: Python deep learning development environment, buntu Server 20.04 LTS operating system.

5.2 Experimental Data

The data for this experiment is sourced from the summary evaluation table of the mathematics department of a certain higher vocational college, which includes electronic images of students' exam papers, as well as training courses in mathematical abstraction, logical reasoning, mathematical modeling, intuitive imagination, mathematical operations, and data analysis. Data of a total of 1032 students is collected for the experiment, and the experimental data is divided into ten-fold cross-validation method to divide the self-built dataset. The experimental data is divided using the ten-fold cross-validation method to partition the self-built dataset, taking turns conducting experiments and taking the average of the results as the final experimental result. The collection of core influencing factors in mathematics is as follows:

(1) In mathematical abstraction and intuitive imagination, experiments provide abstract contexts, collect students' problem-solving processes and ideas, and evaluate their understanding and application abilities in mathematical abstraction.

(2) In logical reasoning and mathematical modeling, experiments evaluate students' logical thinking and modeling abilities by collecting their reasoning and modeling processes and conclusions.

(3) In mathematical operations and data analysis problems, experiments provide relevant questions, collect students' calculation and analysis processes, as well as final results, to evaluate their data analysis and calculation abilities.

In the training courses for various aspects of mathematical core competencies, the corresponding courses for mathematical abstraction are advanced mathematics, linear algebra, etc. The corresponding courses for logical reasoning are discrete mathematics and mathematical logic. The corresponding courses for mathematical modeling are introduction to mathematical modeling, mathematical modeling and simulation. The corresponding courses for intuitive imagination are calculus geometry and spatial geometry. The courses corresponding to mathematical operations are numerical analysis and operations research. The courses corresponding to data analysis correspond to statistics and partial differential equations.

5.3 Experimental Design

Based on the collected mathematics learning data of higher vocational students, the following steps are conducted to carry out the experiment:

(1) Firstly, the raw collected data is preprocessed with image clarity and normalization to facilitate model input.

(2) The MobileNet-V2 model is used to extract features from electronic images of students' math exam papers, and the extracted image features are combined with mathematical core competencies to construct a comprehensive feature representation.

(3) The output features of the MobileNet-V2 model are used as inputs to the collaborative filtering algorithm, and personalized course recommendations are made for students' mathematical core competencies using the collaborative filtering algorithm.

(4) Based on the constructed comprehensive model, an evaluation system is developed for the components of mathematical core competencies. Then 10 experiments are designed to evaluate the mathematical core competencies and personalized recommendation performance of students in various aspects under different algorithms.

5.4 Experimental Results

Based on the above steps, the evaluation results of the core influencing factors of mathematics for students are shown in Table 1. In Table 1, 0-60 is represented by 5; 60-70 is represented by 4; 70-80 is represented by 3; 80-90 is represented by 2; 90-100 is represented by 1.

Table 1. Evaluation of mathematical core competencies

Student number	Mathematical abstraction	Logical reasoning	Mathematical modeling	Intuitive imagination	Mathematical operations	Data analysis
1	1	2	2	2	5	5
2	2	3	5	2	1	1
3	1	5	2	3	2	2
4	5	2	2	5	1	2
5	1	2	1	1	2	5
6	2	2	2	1	5	4
7	3	2	1	5	1	1
8	4	2	1	3	2	1

9	2	5	2	3	4	2
10	1	1	5	3	1	1

From Table 1, it can be seen that Student 1 has the worst performance in mathematical operations and data analysis, both below 60 points, indicating a significant lack of ability in mathematical operations and data analysis. Student 2 performs the worst in mathematical modeling. Student 3 performs the worst in logical reasoning. Student 5 performs the worst in data analysis. Student 7 performs the worst in intuitive imagination. Student 4 performs the worst in both mathematical abstraction and intuitive imagination. Student 6 performs the worst in mathematical operations and also performs poorly in data analysis. Other students all have a certain degree of ability deficiency.

After model evaluation, personalized recommendations are made for students' mathematical core competencies using collaborative filtering algorithms. The results are shown in Table 2. In Table 2, advanced mathematics is represented by 1; linear algebra is represented by 2; discrete mathematics is represented by 3; mathematical logic is represented by 4; introduction to mathematical modeling is represented by 5; mathematical modeling and simulation is represented by 6; calculus geometry is represented by 7; spatial geometry is represented by 8; numerical analysis is represented by 9; operations research is represented by 10; statistics is represented by 11; partial differential equations are represented by 12.

Table 2. Results of personalized recommendations

Student number	Recommended results			
1	9	10	11	12
2	5	6	-	-
3	1	2	3	4
4	1	2	7	8
5	11	12	-	-
6	9	10	12	-
7	7	8	-	-
8	1	-	-	-
9	3	4	9	-
10	5	6	-	-

From Table 2, it can be seen that Student 1 is recommended for courses such as numerical analysis, operations research, statistics, and partial differential equations, which directly supplement Student 1's lack of ability in mathematical operations and data analysis. For Student 8, it can be seen from the evaluation results that there is a certain ability gap in mathematical abstraction, but he has reached a level of 60-70. The system recommends courses that are more targeted for learning advanced mathematics. The recommendation results of other students are personalized course recommendations based on the evaluation results of each student's mathematical competencies, which meets practical needs.

Experimental Discussion

6.1 Evaluation Results of Different Models

To evaluate the performance of the MobileNet-V2 model in evaluating mathematical core competencies, it is compared with EfficientNet (Efficient Network), FBNet (Facebook-Berkeley-Nets), SVM (Support Vector Machine), CNN (Convolutional Neural Network) for analysis, as shown in Figure 3. In Figure 3, the horizontal axis represents different models, and the vertical axis represents the corresponding percentage ratio of accuracy, recall rate and precision of the models.

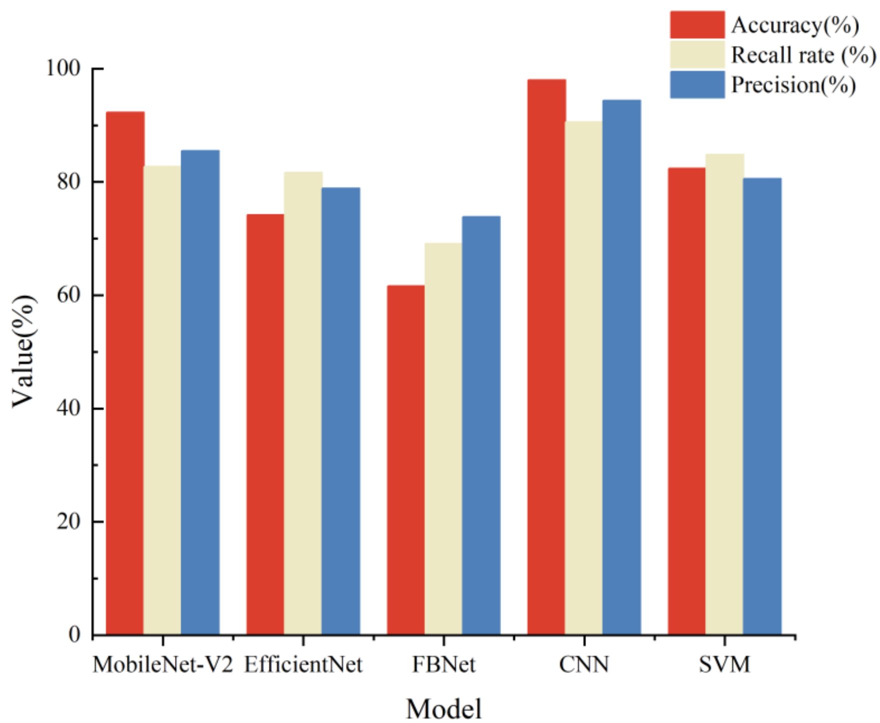


Figure 3. Evaluation results of different models

In Figure 3, there are certain differences in the evaluation of mathematical core competencies among different models, demonstrating different performance. In terms of accuracy, the CNN model achieves 97.98%, while the MobileNet-V2 model achieves 92.32%, indicating that the accuracy of the MobileNet-V2 model is worse than that of the CNN model. This may be because the MobileNet-V2 model fails to consider accuracy to a certain extent while ensuring lightweight. The accuracy of the EfficientNet model reached 74.19%, and that of the FBNet model achieves 61.63%. It can be found that the MobileNet-V2 model performs good among these lightweight models and meets practical needs. In terms of recall and precision, MobileNet-V2 achieves 82.75% and 85.48% respectively, both realizing good performance.

Overall, MobileNet-V2 performs well in evaluating mathematical core competencies, with good feature extraction and classification capabilities, and it can accurately evaluate various aspects of mathematical core competencies.

6.2 Parameter Quantity and System Response Time of Different Models

In this experiment, the parameter quantity and system response time of different models are statistically analyzed, as shown in Figure 4.

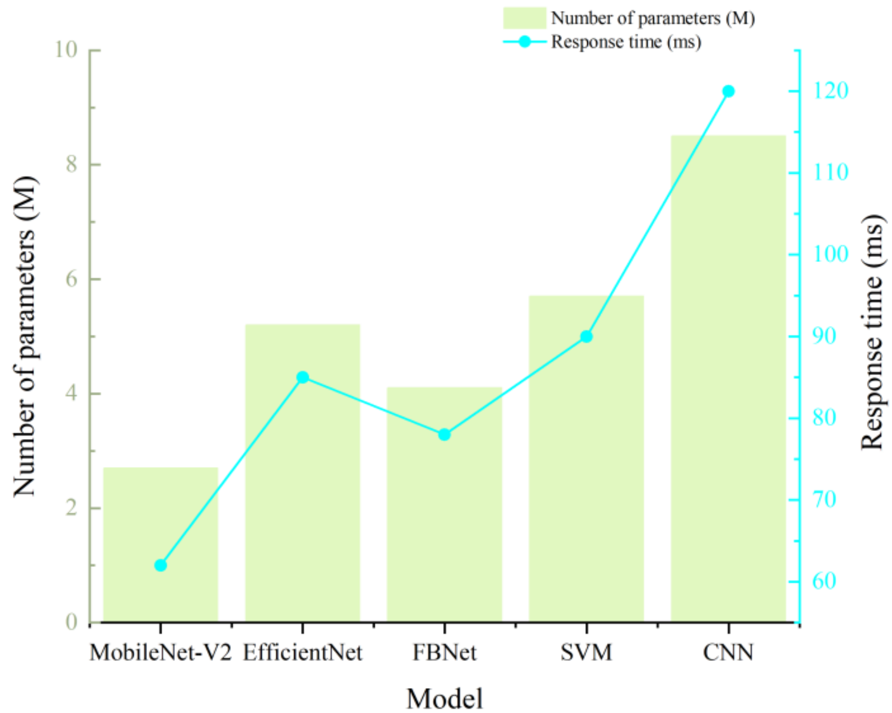


Figure 4. Parameter quantity and response time of different models

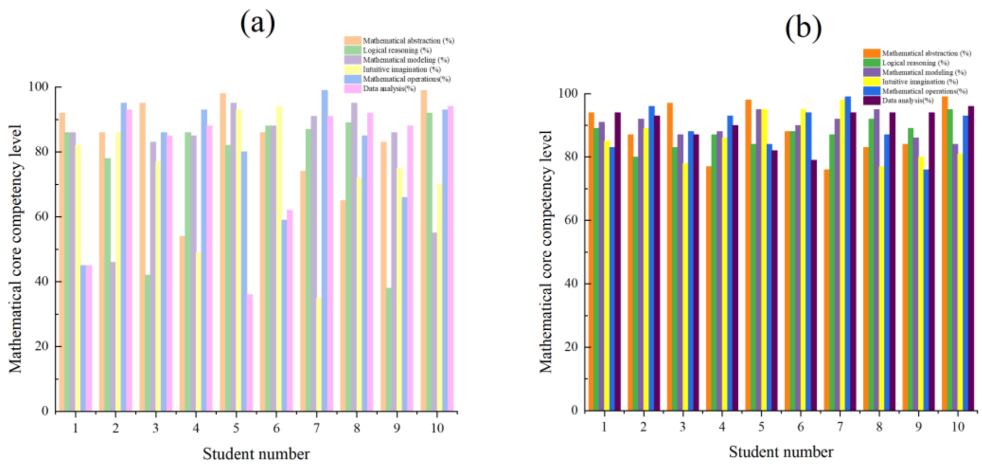
From Figure 4, it can be seen that the MobileNet-V2 model has the smallest number of parameters, only 2.7M, and a response time of 62ms. In contrast, the deep learning model CNN has the largest number of parameters, reaching 8.5M, and a relatively long response time of 120ms. This is because MobileNet-V2 adopts a lightweight deep convolutional network structure, which achieves fewer parameters and faster response speed through techniques such as depthwise separable convolution, making it more suitable for resource constrained edge environments.

EfficientNet and FBNet models achieve average levels in terms of parameter quantity and response time. The EfficientNet model has a parameter number of 5.2M and a response time of 85ms, demonstrating a certain degree of balance. Although the SVM model has a large number of parameters, its response time is relatively short compared to CNN, mainly because the inference process of the SVM model is relatively simple and does not require complex calculations and a lot of parameter adjustments.

Based on the above, the MobileNet-V2 model achieves a balance between model performance and resource consumption to meet practical needs.

6.3 Core Competency Level of Students before and after Learning Recommended Courses

After personalized recommendation, in order to compare the improvement of students' core competency level, a comparative analysis is conducted on the core competency level before and after learning the recommended courses, as shown in Figure 5. In Figure 5, Figure 5(a) presents the core competency level of 10 students before learning the recommended courses, and Figure 5(b) presents the core competency level of the 10 students after learning the recommended courses.



Mathematical core competency level of students before learning the recommended courses

Mathematical core competency level of students after learning the recommended courses

Figure 5. Core competency levels of students before and after learning recommended courses

From Figure 5(a), it can be seen that Student 1 only scores 45 points in mathematical operations and data analysis, indicating a lower score. Student 2 only scores 46 points in mathematical modeling and fails. Student 3 only scores 42 points in logical reasoning. Student 4 only scores 54 and 49 in mathematical abstraction and intuitive imagination, respectively. Student 5's data analysis is poor, only scoring 36 points. Other students all lack certain abilities in various aspects of mathematical core competencies.

In Figure 5(b), the core competency levels of all 10 students improve after learning the recommended courses. Student 1 scores 83 and 94 in mathematical operations and data analysis, respectively, indicating a significant improvement and confirming the effectiveness of the recommended course. Student 2 achieves a score of 92 in mathematical modeling, with an improvement of 46 points compared with that before learning the recommended courses. Student 3 achieves a score of 83 in logical reasoning. Student 4 scores 77 and 86 in mathematical abstraction and intuitive imagination, respectively. Student 5 scores 82 in data analysis. Other students improve after learning the corresponding recommended courses, indicating that the matching degree of the recommended courses is quite high, which are in line with the actual needs of students.

Overall, there has been a certain improvement in the core competency level of students before and after learning the recommended courses, and the core competency level of students after learning the recommended courses is not lower than that of students before learning the recommended courses.

6.4 Evaluation of Personalized Recommendation Performance

To further explore the performance of personalized recommendations, the item-based collaborative filtering algorithm used in the experiment is compared with content-based collaborative filtering algorithm, singular value decomposition (SVD) method, and association rule mining method for analysis in terms of recommendation accuracy, diversification, and coverage, as shown in Figure 6.

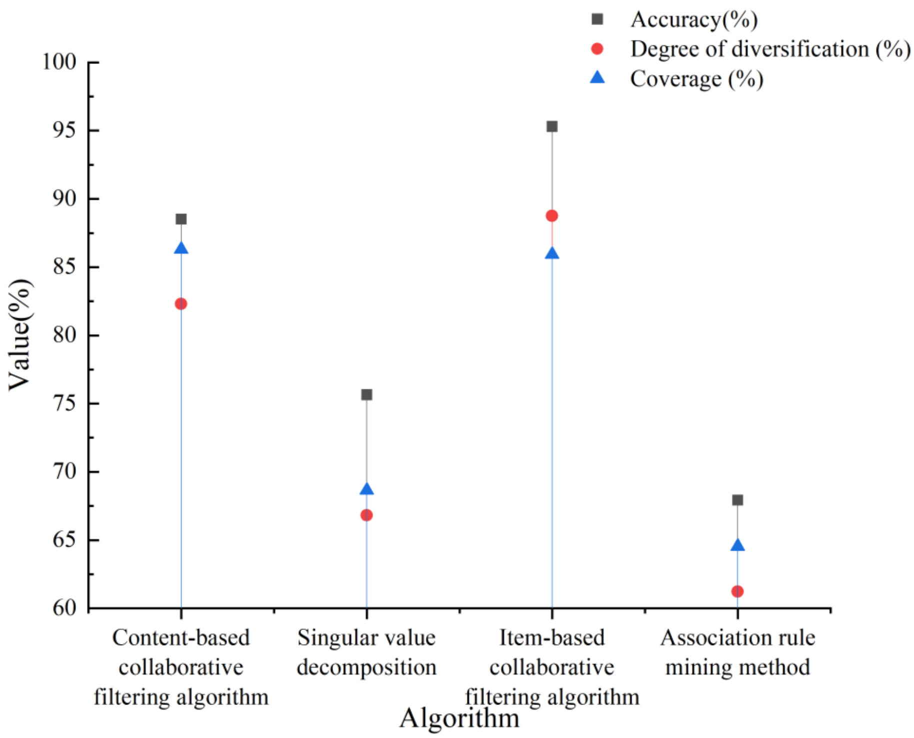


Figure 6. Personalized recommendation performance

In Figure 6, from the perspective of recommendation accuracy, the item-based collaborative filtering algorithm performs the best with an accuracy of 95.31%, followed by the content-based collaborative filtering algorithm with an accuracy of 88.52%. The accuracy of singular value decomposition method and association rule mining method are 75.65% and 67.93%, respectively, which are relatively low. In terms of diversification, the content-based collaborative filtering algorithm reaches 82.32%, while item-based collaborative filtering algorithms reaches 88.77%, with an improvement of 6.45% compared to content-based collaborative filtering algorithm. In terms of coverage, the performance of item-based collaborative filtering algorithm and content-based collaborative filtering algorithms is relatively close, both of which are high, while singular value decomposition and association rule mining algorithms are low.

Overall, the item-based collaborative filtering algorithm achieves good performance in terms of recommendation accuracy, diversification, and coverage. There are significant differences between different algorithms, mainly because the item-based collaborative filtering algorithm and the content-based collaborative filtering algorithm analyze user historical behaviors or content attributes for recommendations with high accuracy, while singular value decomposition and association rule mining methods are limited by data dimensions and scales, resulting in low accuracy and diversification of recommendation results.

6.5 Resource Utilization Rate

To further explore the adaptability of the system designed in the experiment in edge environments and analyze its application effects, a comparative analysis is conducted on the utilization rate of system resources, as shown in Figure 7. In Figure 7, Figure 7(a) presents the resource utilization of CPU (Central Processing Unit) and memory, and Figure 7(b) presents the resource utilization of Internet and storage resources.

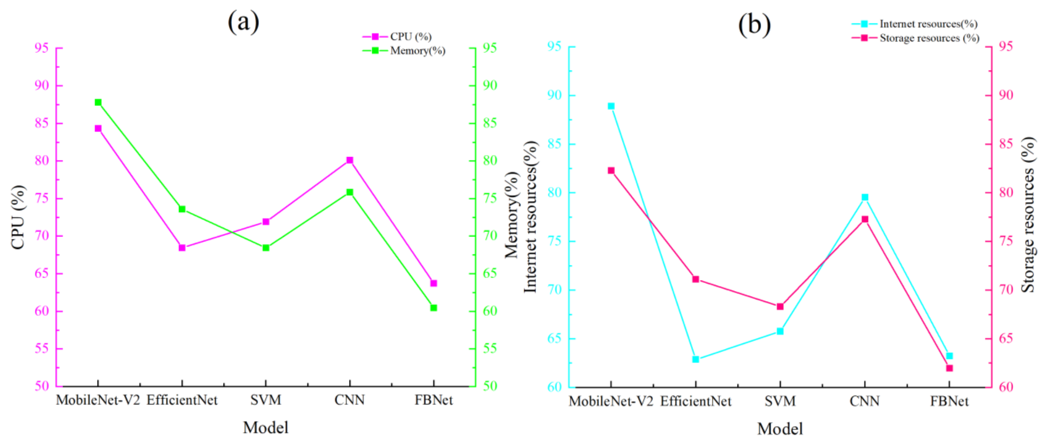


Figure 7. Resource utilization rate

In Figure 7, it can be seen that the MobileNet-V2 model has relatively high CPU utilization, memory utilization, and Internet resource utilization, with rates of 84.35%, 87.82%, and 88.91%, respectively. Its storage resource utilization rate is 82.28%. The EfficientNet model has relatively low resource utilization rates in all aspects, at 68.47%, 73.59%, 62.88%, and 71.13%, respectively. The CNN model shows stable performance in various resource utilization rates, approaching 80%.

Overall, the MobileNet-V2 model demonstrates good resource utilization performance in the system, fully utilizing resources. This is because the MobileNet-V2 model is relatively lightweight and adopts techniques such as depthwise separable convolution, which reduces the number of parameters and computation as much as possible while maintaining high accuracy, resulting in relatively high resource utilization.

6.6 Degree of Impact of Mathematical Core Competencies

The components of mathematical core competencies include multiple aspects, including mathematical abstraction, logical reasoning, mathematical modeling, intuitive imagination, mathematical operations, and data analysis. The impact of different aspects on the level of mathematical core competencies varies, and statistical analysis is conducted, as shown in Figure 8.

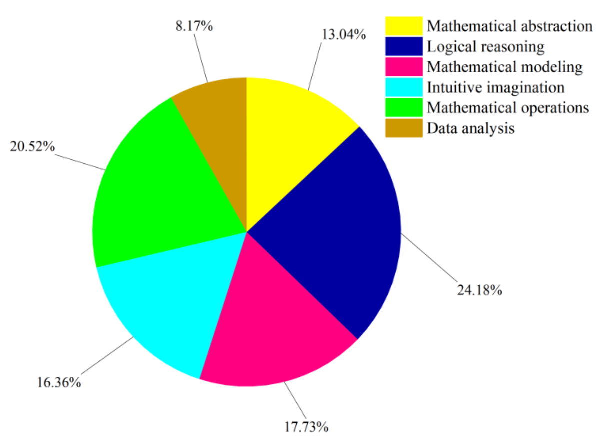


Figure 8. Degree of impact of mathematical core competencies

In Figure 8, it can be seen that the influence of logical reasoning and mathematical operations on mathematical core competencies is relatively high, at 24.18% and 20.52%, respectively. It can be known that in higher vocational mathematics education, it is crucial to attach importance to cultivating students' logical reasoning and mathematical operation abilities, which have a great impact on the level of mathematical core competencies, because logical reasoning ability can help students understand the logical relationship of mathematical problems, and good mathematical operation ability can help students efficiently solve mathematical calculation problems. The impact of mathematical abstraction and mathematical modeling is slightly lower, at 13.04% and 17.73%, respectively. Mathematical abstraction ability is the key for students to understand abstract mathematical concepts and methods, and mathematical modeling ability is the ability to apply mathematical knowledge to practical problems, which plays an important role in cultivating students' innovative thinking and problem-solving abilities.

The impact of intuitive imagination and data analysis on mathematical core competencies is relatively low, at 16.36% and 8.17%, respectively. Although the impact is relatively low, these two aspects are still an indispensable part of mathematical core competences, which is of great significance for cultivating students' comprehensive development and application of mathematical abilities.

CONCLUSION

This article assesses the core competency level of higher vocational mathematics and recommends personalized courses based on edge computing and lightweight computing. According to the collected mathematical learning data, the MobileNet-V2 model is used to evaluate the mathematical core competencies of each student, and personalized course recommendations are made using an item-based collaborative filtering algorithm. This significantly improves the degree of personalization and the level of mathematical core competencies of students, while also demonstrating good adaptability to edge-constrained environments. However, there are still some shortcomings in this article. In data collection, the data in this experiment only comes from one college, and there are certain limitations to student data. Moreover, this article does not fully integrate text data. In the future, the data sources can be expanded, and various types of data can be combined to explore more lightweight models for evaluating and analyzing the level of comprehensive mathematical core competencies.

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