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Research article

The educational resource management based on image data visualization and deep learning

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ABSTRACT

In order to address issues such as inaccurate education resource positioning and inefficient resource utilization, this study optimizes the Educational Resource Management System (ERMS) by combining image data visualization techniques with convolutional neural networks (CNNs) technology in deep learning. Firstly, the crucial role of ERMS in education and teaching is analyzed. Secondly, the application of image data visualization techniques and CNNs in the system is explained, along with the associated challenges. Finally, by optimizing the CNNs model and system architecture and validating with experimental data, the rationality of the proposed model is confirmed. Experimental results indicate a significant improvement in various performance metrics compared to traditional models. The recognition accuracy on the Mnist dataset reaches 98.1 %, and notably, on the cifar-10 dataset, the optimized model achieves an accuracy close to 98.3 % with improved runtime reduced to only 640.4 s. Additionally, through systematic simulation experiments, the designed system is shown to fully meet the earlier requirements for system functionality, validating the feasibility and rationality of the model and system in this study. Therefore, this study holds high practical value for optimizing ERMS and provides meaningful insights into image data visualization techniques and CNNs optimization.

1. Introduction

In recent years, the importance of education resource management systems in the field of education and teaching has become increasingly prominent. With the continuous advancement of digital transformation, image data plays a crucial role in education resource management [1]. Utilizing image data visualization techniques and deep learning methods, especially convolutional neural networks (CNNs), can more accurately locate, analyze, and optimize educational resources [2]. However, traditional education resource management systems face many challenges in handling large amounts of data, such as inaccurate positioning and low resource utilization efficiency. Therefore, this study aims to optimize the education resource management system by combining image data visualization techniques with CNNs to address the existing problems and fully explore the potential value of data.

The important role of the Educational Resource Management System (ERMS) in education and teaching is analyzed, and the application of image data visualization technology and CNNs in this system and the existing problems are discussed. The CNNs model is optimized, and a system and framework are established, with the effectiveness of the model being tested through experiments. The contribution of this study is to improve the quality and effectiveness of education and teaching by accurately positioning and efficiently utilizing educational resources. Teachers and students can more conveniently access appropriate educational resources, and improve the interactivity and personalization level of teaching.

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2. Literature review

In the study of visualization technology, Wenk et al. (2023) devised a visualization system tailored for a web-based robot operating system. This system adeptly handled the reception, parsing, calibration, and pose estimation of robot data, facilitated by its modular and scalable processing modules [3]. In a separate study, Huang et al. (2021) showcased a methodology for extracting image features utilizing the binary encoding attributes of Android applications. This approach involved converting binary files into grayscale images and leveraging the CNNs classification system to identify Android malware [4]. Additionally, Kiranyaz et al. (2021) introduced a second-order convolutional module designed to effectively capture one-dimensional convolution and second-order statistical properties. This module aimed to enhance feature representation and was adaptable for integration into end-to-end network architectures [5].

It can be found that traditional research usually relies on users to manually enter keywords for search, which limits the accuracy and diversity of resources. Furthermore, resource names and descriptions can be inconsistent, complicating resource location. Meanwhile, due to the large number and diversity of resources, traditional methods cannot effectively use and manage these resources. Manual processing and labeling processes are time-consuming and error-prone, making it difficult to meet the needs of fast acquisition and efficient use of resources. In this study, image data visualization technology is used to advance the accuracy and diversity of educational resources. Through the image processing of educational resources, the characteristics of resources can be displayed more intuitively, and more attractive and rich resource choices can be provided to users.

3. ERMS optimization based on image data visualization and CNNs

3.1. The role of ERMS in education and teaching

ERMS is an ERM platform based on computer technology, which provides multiple applications for school education and teaching [6]. Its role is primarily manifested in three aspects. First is resource integration, consolidating scattered resources onto a single platform for convenient retrieval and use. Second is resource sharing, promoting the sharing of educational resources to enhance resource utilization efficiency. Finally, personalized learning involves recommending suitable learning resources based on students' learning needs and progress. The first is the management and promotion of teaching resources. Educational resources refer to various resources utilized in the educational process, including but not limited to teaching materials, course content, books, multimedia resources, software, hardware, facilities, as well as the knowledge and skills of teachers and learners themselves. For example, the books, e-books, online courses, computers, and internet access available in a school library can be considered educational resources. Managing educational resources involves planning, organizing, guiding, coordinating, and controlling these resources to ensure effective utilization and continuous updating. ERMS can carry out centralized digital management of colorful teaching resources, including electronic books, videos, images, audio, etc., so teachers can better utilize and present these resources [7]. Meanwhile, ERMS can also use promotion tools, such as subject portal websites, blogs, etc., to widely promote the resources for teaching to teachers of various subjects. In this way, teachers can better share and communicate using teaching resources. The second is the improvement of teaching quality. Supporting the management and promotion of digital resources is conducive to improving teaching quality [8]. ERMS can help teachers provide more comprehensive teaching resources to meet the learning needs of different students, thereby improving students' learning interests and efficiency and promoting teaching quality. The third is online learning for students. Through ERMS, students can use electronic devices to learn teaching resources online anytime and anywhere [9]. Students can search and download courseware and materials from the platform and view online course videos and tests. These can help students strengthen their self-learning and practical operation abilities and actively participate in teaching activities [10]. For example, an ERMS in a school may allow teachers to upload teaching materials and videos. Students can access and study these materials based on their learning progress, while the system recommends supplementary materials corresponding to the students' learning situations. The last is educational resource-assisted assessment. Through ERMS, teachers can use various assessment tools to help evaluate students' learning situations and teaching effects, and integrate the assessment results in time, to advance the teaching methods and teaching quality accordingly [11].

In a word, ERMS can help schools effectively manage and utilize comprehensive educational resources and strengthen the communication and interaction between teachers and students. Furthermore, students' interests in learning and teaching quality are further improved, making positive contributions to the development and progress of education [12].

3.2. The application of CNN in the resource management system

CNN is a famous deep learning model whose name comes from the fact that convolution operation is introduced into this model [13]. CNN can be classified as a multi-layer feedforward neural network (FNN) model. But different from the traditional multi-layer FNN, the input of CNN is a two-dimensional mode. Moreover, its connection weight is a two-path matrix, and its basic operations are two-dimensional discrete convolution and pooling [14]. Currently, CNN has been successfully applied in many fields, such as target detection, image classification, and target tracking. Its essential components include convolutional, pooling, and fully connected layers [15]. The traditional CNN structure is shown in Fig. 1.

In general, each convolutional layer consists of several nodes. The convolutional layer extracts different features of the image through convolution operation. The input of the nodes of the convolutional layer is the feature map because the feature map is formally a two-dimensional matrix [16]. Then each convolution kernel matrix is convolved with its corresponding input feature map to obtain a

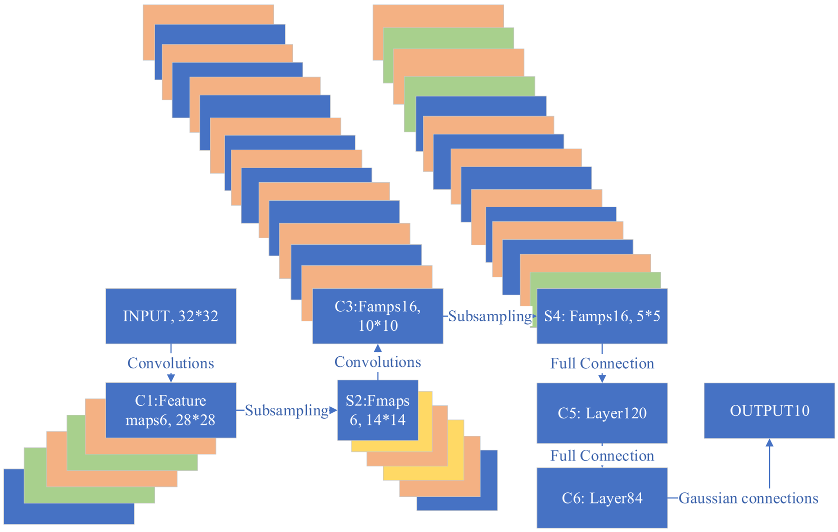

Fig. 1. CNN structure.

two-dimensional pattern. These matrices are then summed and biased as input to the activation function, resulting in the output feature map of the node. The output of the node reads:

$$x_j^l = f\left(\sum_{i=1}^{m_i} x_j^{l-1} * k_j^l + b_j^l I\right) \tag{1}$$

x_j^l and x_j^{l-1} are feature maps of the l and $l-1$ layers, respectively; I means a matrix with all elements of 1; b_j^l refers to the bias of node j of the l layer; k_j^l indicates a learnable convolution kernel matrix, and m_i represents the number of matrices. Generally, the convolution kernel is a small matrix of 3*3 or 5*5. When doing convolution operations, the convolution kernel is connected to a local region of the corresponding feature map, called the local receptive domain of the convolution kernel. The whole feature map shares the weight of the convolution kernel, which is called weight sharing [17].

As for the convolutional layer, the study focuses mainly on the activation function. The activation function plays a vital role in CNN. It introduces nonlinear properties into the network, which is a crucial factor in ensuring the uniform approximation ability of the network [18]. Additionally, since most training algorithms of FNNs are based on the idea of error backpropagation, the activation function's property greatly influences the calculation of gradient [19]. For example, the activation function's output saturation seriously affects the network's convergence. The higher the output saturation, the worse the network's convergence. Hence, the activation function has a significant influence on the training speed or convergence of CNN. The stability of neural network training generally depends on limiting the variables in the network to a certain range. The activation function acts as a restriction of network variables, so it also has an important impact on the stability of network training. In short, the activation function significantly affects the convergence, stability, and uniform approximation ability of the network [20]. Common activation functions are as follows:

$$Sigmoid = \frac{1}{1+\mathrm{e}^{-x}} \tag{2}$$

$$Tanh = \frac{\mathrm{e}^{2x}-1}{\mathrm{e}^{2x}+1} \tag{3}$$

$$ReLU = max(0, x) \tag{4}$$

$$PReLU = max(x, ax) \tag{5}$$

Sigmoid, *Tanh*, *ReLU*, and *PReLU* are all activation functions; e refers to a constant, x stands for the input; *max* represents the maximum value; a means the calculation parameter. The Sigmoid function produces an output ranging between 0 and 1, frequently employed for probability estimation in the output layer. Nonetheless, within deep networks, it is susceptible to the vanishing gradient dilemma, potentially impeding the learning process during training. Tanh function yields values spanning from -1 to 1, exhibiting a broader range than the Sigmoid function, thereby potentially enhancing performance in certain scenarios. Nevertheless, it remains vulnerable to the vanishing gradient problem, particularly in deep networks. ReLU stands out as one of the most prevalent activation functions, notably in CNNs, by setting all negative values to zero while preserving positive values. This nonlinear formulation aids in hastening the training pace and augmenting performance. Nonetheless, ReLU confronts the issue of dormant neurons, wherein a neuron halts updating once its input turns negative during training. PReLU emerges as an enhanced iteration of ReLU, permitting slight

Table 1
Comparison of visual image tools.

Can draw images	Echart	Highcharts	Jfreechart	Excel
Histogram	√	√	√	√
Bar chart	√	√	√	√
Line chart	√	√	√	√
Scatter plot	√	√	√	√
Curved surface graph	×	√	×	×
Dynamic type switching	√	×	×	×

negative slopes instead of instantaneously nullifying negative values. These marginal negative slopes serve as trainable parameters, empowering the network to adjust its activation function configuration and alleviate the problem of dormant neurons. Consequently, the activation function opted for in this study is the PReLU function. Relative to alternative activation functions, PReLU finds extensive application in image recognition tasks owing to its simplicity and efficacy, thereby further enhancing model performance. Compared to other models, CNN is specifically designed to handle data with distinct hierarchical or spatial relationships, such as image data. The local patterns in an image, such as edges, corners, and textures, are crucial for understanding the overall content of the image. CNN can efficiently capture these local patterns through its convolutional layers. And in CNN, convolution operations recognize specific features in the image by repeatedly using the same weights throughout the entire image. This parameter sharing mechanism greatly reduces the complexity of the model and the number of training parameters, making CNN more efficient in image recognition tasks than other deep learning models.

3.3. Application of image data visualization technology in the resource management system

Image data visualization technology refers to the technique of transforming data into images or charts for a more intuitive understanding and analysis. For example, displaying students' performance data through bar graphs or line charts can assist teachers and students in quickly comprehending the distribution and trends of grades [21]. Data visualization is a constantly developing and changing research content. Its content scope is continuously expanding [22]. Data visualization technology is a relatively high-end technical content. This technology preprocesses, cleans, and processes data, and visually displays data through graphic images, data processing, data vision, and user display interfaces. Besides, it is through data expression, modeling, data surface, three-dimensional data, data attributes, animation, or chart forms [23]. The technology is chiefly to show the content of the educational administration database in front of users clearly by means of graphics. Now, the market's more popular graphic and image report tools mainly involve Echart, Highcharts, Jfreechart, Excel, and others. These tools can generate pie charts, histograms, bar charts, line charts, and so on through data [24]. Some of their performance comparisons are exhibited in Table 1.

The relationship between image data visualization and CNNs is a multidimensional complementary process. It not only enhances the experimental understanding of the model's working principles but also improves the model's performance and transparency. Through feature visualization, CNNs can automatically learn the feature representations of images, and this process can be intuitively demonstrated through image data visualization techniques. This visualization aids researchers and developers in gaining a deeper understanding of how CNNs identify and process basic elements such as edges and corners in images. For instance, visualizing the model's convolutional layers can show how the model captures image features. Data mining (DM) usually refers to using multidimensional data modeling in a large amount of data through the association relationship between the attributes of various data items. A data relationship is formed between each data item. After data cleaning and data summary, DM results are obtained [25]. With the advent of the era of big data, DM technology will be more widely developed. DM has been commonly used in all walks of life, such as data statistics, data collection & evaluation, network traffic analysis, online transaction analysis, data prediction & early warning, financial & log data analysis, etc. As long as there is a certain amount of data in various fields, it can be analyzed by DM technology, and the results can be acquired. The improvement of personal business is aided by the mined data results [26]. This study is about the application of data visualization technology in the educational administration database. The main data content of the analysis is the educational administration database. The existing data of the educational administration database is mined and analyzed. The mined data is displayed through data visualization technology to help the educational administration's teaching work. At present, the application of DM technology in educational affairs is relatively few [27]. DM is rarely used in educational administration in universities. The educational management system of universities is insufficient in analyzing students' grades, and course selection, especially the analysis of students' teaching evaluation. DM can analyze this educational administration data information to obtain more data results, and then display data results by visualization technology [28].

3.4. ERMS optimization using image data visualization and CNN application

Currently, in traditional systems, the classification of electronic resources in school libraries is chaotic, making it difficult for students and teachers to find the required reference materials. Therefore, optimization is carried out to address the issue of inaccurate resource location. For instance, libraries adopt advanced classification and retrieval systems where users can quickly locate specific resources through various means such as keywords, authors, and publication years. Additionally, when preparing courses, teachers may unknowingly duplicate similar teaching materials due to a lack of awareness of existing resources. With ERMS, teachers can view

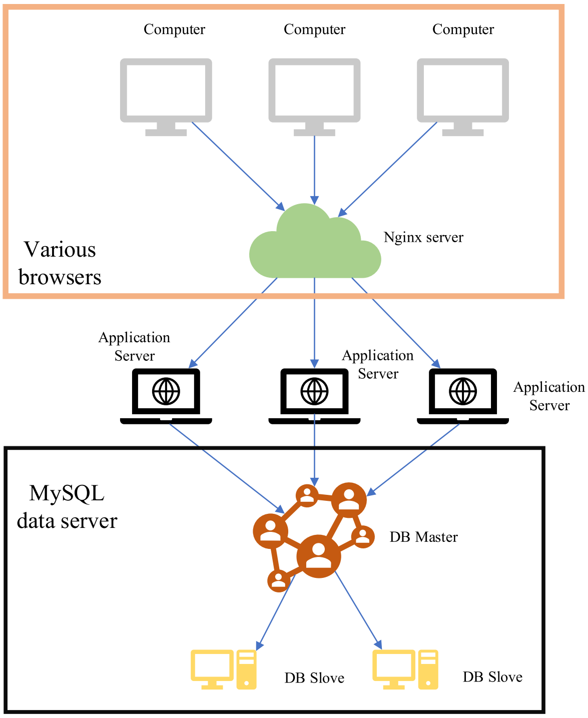

Fig. 2. System application deployment optimized in this study.

the teaching resources already available within the school, avoiding redundant work and saving time and resources. To achieve accurate resource location, certain steps need to be followed. Firstly, it requires an analysis of the current situation, identifying the shortcomings of the existing resource location system, which forms the foundation for problem discovery. Subsequently, conducting needs research is essential to thoroughly understand users' specific requirements and usage habits during resource retrieval, ensuring that optimization measures effectively address users' actual issues. Based on the research findings, system optimization becomes a necessary step, which may involve updating metadata, improving search algorithms, etc., to enhance the accuracy and efficiency of resource location. To ensure that users can fully benefit from the optimized system, user training is indispensable, helping improve users' retrieval efficiency. Finally, through continuous feedback and improvement, collecting user feedback and making ongoing adjustments and improvements to the system is crucial for continuously optimizing the accuracy of resource location and user experience.

Simultaneously, in order to achieve efficient resource utilization from inefficient usage, it is necessary to assess the current resource utilization, identify wasteful and inefficient aspects in resource use, which helps clarify the direction for improvement. Subsequently, establishing a resource-sharing mechanism is critical by creating a resource-sharing platform to promote sharing and reuse, thereby enhancing the overall utilization of resources. Optimizing resource allocation is also necessary, requiring the rational distribution and scheduling of resources based on the actual needs of teaching activities to ensure effective utilization at the right time and place. In addition, raising awareness of resource utilization through training and publicity, enhancing teachers' and students' awareness of resource conservation and efficient utilization, forms the basis for developing good resource utilization habits. Lastly, through technical support and innovation, adopting new technologies and methods such as artificial intelligence recommendation systems can further improve the efficiency of resource use, achieving the maximization of resource utilization.

According to the characteristics of the application of data visualization technology in educational administration information databases, the design idea of software engineering is to improve the function of each module while maintaining the structure [29]. The most basic login management, student course selection, student achievement, student-teacher classroom evaluation, and other modules should be involved. The optimized system architecture is plotted in Fig. 2.

The system adopts a large distributed architecture design for planning and design. The system is divided into a proxy server, an application server, and distributed database server. Through the Nginx front-end proxy, requests for projects are uniformly forwarded to different application servers. The application server in this project principally adopts Tomcat, and Jetty, Web Logic, or other Java containers can also be used. The database assumes the My Structured Query Language (MySQL) server and is implemented using MySQL's distributed technology. The input of data is initiated by front-end users through internet browsing devices, generating requests that may include data queries, data submissions, page requests, etc. This encompasses configuration information and current status details of proxy servers, application servers, and distributed database servers. These details are crucial for decision-making regarding the routing and handling of requests. The output of data, after being processed by the application server, is returned to the front-end users. This includes reports on metrics such as processing time, resource utilization, and system throughput. Because the

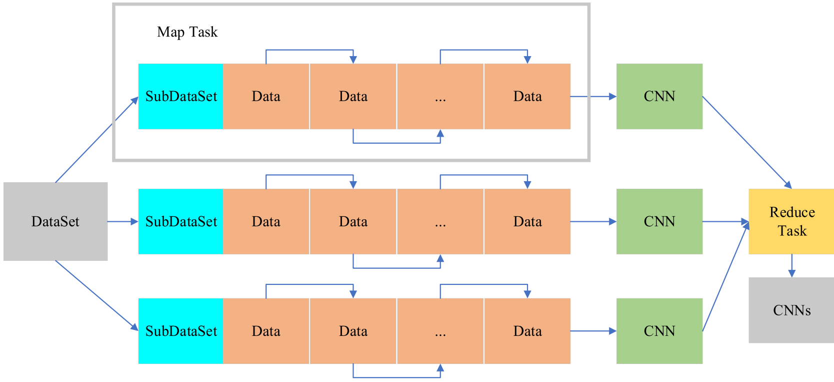

Fig. 3. The optimized CNN.

Table 2
Experimental environment.

Software and hardware	Experimental configuration
Operating system	Win7
Server operating environment	Tomcat6.0
Browser	IE8.0
Memory	64G
Hard disk	2T
Front-end proxy server	Nginx server

system framework adopts a distributed framework, distributed parallel processing can be used here when a problem can be decomposed into multiple sub-problems that are independent. Finally, merging the processing results can greatly improve efficiency. Through distributed parallel processing and proper load balancing, the primary goal of optimization is to reduce the response time for user requests, enhancing the system's processing speed and efficiency. Optimization also considers how to improve the system's scalability and reliability through the design of a distributed architecture, ensuring that the system maintains high performance even when the load increases.

Similar to traditional neural networks, CNN is also based on a standard Back Propagation (BP) algorithm, which is a typical serial calculation process. Each round of training can be summarized into three steps: forward propagation of sample data, backward propagation of sensitivity variables, and adjustment of network parameters. It can be seen that the parameters of CNN will change after each training. That is to say, the latter training depends on the previous training results, and the training process of the whole neural network cannot be divided into independent sub-problems. Thus, the traditional CNN algorithm is difficult to parallelize. Therefore, this study optimizes the model through the Map Reduce process, and the optimized neural network model is presented in Fig. 3.

The Data Set is divided into 5 parts, and each Map Task is used as a CNN training model to train 5 pieces of data respectively. In the reduce stage, 5 CNN classifier model parameters are output. For the same example, the algorithm is utilized to integrate the classification effect of 5 CNN classifiers to achieve the purpose of improving the accuracy.

4. Performance analysis of ERMS based on data visualization and CNN model

4.1. Comparison of accuracy and running time of the optimized model

In this experiment, six datasets are selected. They are the Canadian Institute for Advanced Research 10 (cifar-10), Modified National Institute of Standards and Technology (MNIST), Canadian Institute for Advanced Research 100 (cifar-100), Image Net, Pattern Analysis, Statistical Modeling and Computational Learning Visual Object Classes (PASCAL VOC), and Mnist handwritten database. These datasets cover various types of images ranging from simple to complex, including handwritten digits (MNIST and Mnist handwritten database), object classification (CIFAR-10 and CIFAR-100), and complex scenes and objects (ImageNet and PASCAL VOC). This diversity ensures that the model's generalization ability and adaptability are tested across different image recognition tasks. These datasets are widely recognized standard test platforms in the fields of deep learning and computer vision. They provide a common set of standards that can be used to assess and compare the performance of different models and technologies. By testing on these widely acknowledged datasets, researchers can directly compare the effectiveness of their methods with existing technologies. In this study, 5000 randomly selected 32×32 color images from each dataset are used as the training set, and another 5000 32×32 color images are used as the sample set. The images from these sample sets and training sets will be input into the model as input data, and the output content of the model will also be color images. The experimental environment is outlined in Table 2.

Since the image is not easy to read directly into the system, the image is preprocessed and all datasets are stored in a text file in the

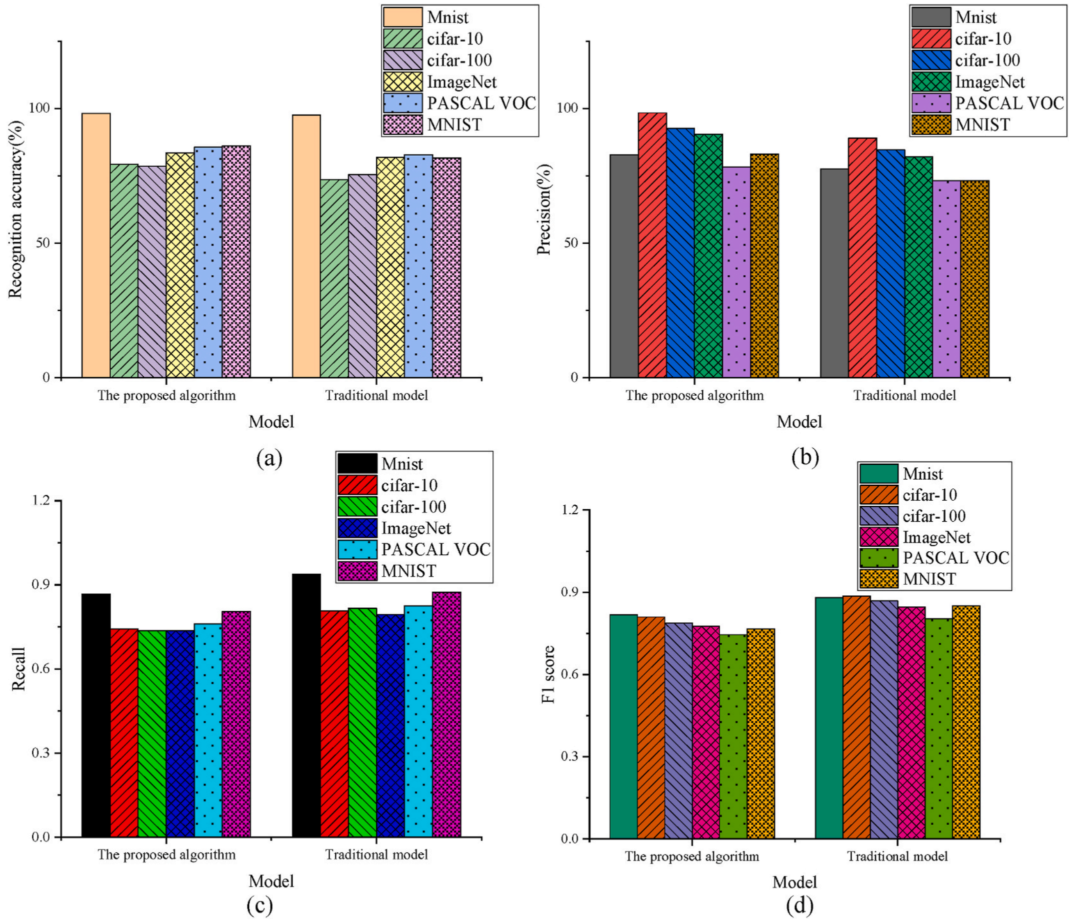

Fig. 4. Comparison of Model Performance in Different Datasets (a) Accuracy; (b) Precision; (c) Recall; (d) F1 score.

form of a pixel gray value. One line of the file represents a picture. The indicators for experimental comparison include accuracy, precision, F1 score, and recall. Among them, accuracy is compared with actual images to demonstrate the accuracy of the optimized model. By conducting recognition experiments using the input sample set, the model's various performances across different datasets are illustrated in Fig. 4.

From Fig. 4 (a) and 4 (b), it can be seen that, in the Mnist dataset, the optimized model performs well in recognition accuracy. Compared with the traditional model, the recognition accuracy of the traditional model is 97.5 %, while that of the proposed optimization model is 98.1 %. Additionally, no matter in the Mnist dataset or other datasets, the recognition accuracy of the optimized model is significantly better than that of the traditional model, with the highest and the lowest difference of 5.7 % and only 1.4 %. The optimized model consistently outperforms the traditional model in accuracy across all datasets. Especially on the cifar-10 dataset, the accuracy of the optimized model approaches 98.3 %, compared to the traditional model's accuracy of 89 %. This indicates a significant performance improvement of the optimized model in handling complex image classification tasks. As can be seen from Fig. 4 (c), in terms of recall, the optimized model also demonstrates higher performance than the traditional model. For instance, in the MNIST dataset, the recall of the optimized model increases from approximately 0.866 to about 0.938, suggesting that the optimized model can more comprehensively identify positive instances, reducing cases of omission. The improved recall on cifar-10 and cifar-100 datasets also indicates that the optimized model has stronger robustness in multi-class complex scenarios, effectively enhancing the model's ability to recognize rare categories. Fig. 4 (d) suggests that, the F1 score, as a harmonic mean of precision and recall, provides a metric for evaluating the overall performance of the model. On all datasets, the F1 score of the optimized model is significantly higher than that of the traditional model, indicating that the optimized model achieves a better balance between precise and comprehensive recognition. The traditional parallel model generates only one CNN classifier. While the optimized parallel model generates one classifier on each node and integrates these classifiers with algorithms to improve the classification accuracy. Specifically, the proposed parallel model integrates several classifiers that can handle different data for better performance. Moreover, generating classifiers at each node enables the model to use hardware resources better, making the calculation faster. Combined with the above characteristics, the optimized model can achieve higher recognition accuracy and faster computing speed.

In conclusion, the optimized model realizes the independent generation of classifiers on each node by taking advantage of parallel computing. These classifiers' results are integrated to obtain faster computation speed and higher recognition accuracy. Through

Table 3
Comparison of running time in various datasets.

	Mnist	cifar-10	cifar-100	ImageNet	PASCAL VOC	MNIST
The proposed algorithm	640.4	711.4	830.3	8423.6	1361.5	1136.6
Literature [30]	669.2	745.3	836.9	8763.6	1742.2	1432.4
Literature [31]	701.2	772.5	852.1	8859.9	1660.5	1335.2

Table 4
Performance test results.

Number of users	Average response time (seconds)	Processing success rate (%)
10	0.5	100
50	0.7	100
100	0.9	99
200	1.2	98

experiments, the proposed model is more accurate and effective than the traditional model, which is expected to bring more outstanding performance in the field of image recognition. The shorter the runtime, the faster the computational speed of the model. The comparison results of the running time of the two models are portrayed in Table 3.

Table 3 reveals that the optimized model proposed in this study is significantly better than the traditional parallel model regarding running time. Specifically, it is found through research that the traditional parallel model usually needs a large number of training rounds to achieve the ideal effect due to the low frequency of weight update, so its training time is relatively long. Additionally, this model needs to process a large amount of intermediate data, which may even exceed the original dataset's size, markedly reducing its efficiency. In the proposed optimization model, the dataset is distributed to different nodes for independent operation, avoiding generating and transmitting intermediate data. Moreover, the updating operation of ownership value is completed within the nodes, reducing inter-node communication overhead. This distributed running mode effectively utilizes computing resources and further improves the training efficiency and performance of the model. For example, in the Mnist database, the minimum running time of the proposed optimized model is only 640.4s, while the traditional parallel model requires a much longer running time. This proves that the proposed optimization model can effectively enhance the operating efficiency of the model, which is of great significance for researchers and engineers in practical applications.

4.2. ERMS testing

To further validate the performance of the optimized model in practical applications, this study conducted ERMS detection experiments as follows.

(1) Clearly Define the Detection Objectives:

The objective is to assess the performance of the ERMS optimized through the fusion of image data visualization techniques and CNNs in terms of performance, data accuracy, functional integrity, and user experience.

(2) Establish Testing Criteria:

Performance: System response time should be less than 1 s.
Data Accuracy: Image data recognition accuracy should exceed 98 %.
Functional Integrity: All expected functions should operate without any faults.
User Experience: User satisfaction ratings should be above 4 (out of 5).

(3) Prepare Testing Data:

Testing data comprises various types of educational resource images and related information, simulating real-world usage scenarios.

(4) Conduct Functional Testing:

Test the system's resource search, data visualization, and statistical analysis functions. Results indicate that all functions operate as expected.

(5) Performance Testing:

Table 5
User experience evaluation results.

Evaluation Criteria	User Satisfaction Rating
Interface Friendliness	4.3
Logical Functionality	4.2
Navigational Ease	4.1
Information Display Clarity	4.4

Utilize load testing to simulate different workloads, assessing the system's response speed and concurrent processing capabilities. Test results are presented in Table 4.

(6) Data Accuracy and Integrity:
The system achieves recognition accuracies of 98.1 % and 98.3 % when processing the MNIST and CIFAR-10 datasets, respectively.

(7) User Experience Assessment:
Evaluation of user satisfaction regarding the system interface, functional flow, navigation, and information display. Results are presented in Table 5.

(8) Security Evaluation:
The system's security mechanisms, including identity authentication, permission management, and data encryption, meet the expected standards.

(9) Summary and Improvement:
The test results indicate that the optimized ERMS performs well in the vast majority of cases. However, there is a slight increase in response time under high concurrency conditions. This can be addressed in the future by further optimizing algorithms and increasing server resources.

5. Conclusion

The swift growth of information technology and the wide popularization of the Internet make the acquisition and management of educational resources more convenient. However, there are still some problems, such as inaccurate resource positioning and inefficient resource utilization. Therefore, this study aims to explore how to combine image data visualization technology with CNN technology to solve the related problems in ERM. This study first introduces the role of ERMS in education and teaching, then explains the image data visualization technology, the application of CNN in ERMS, and the existing problems. Finally, the CNN model and system architecture are optimized. The rationality of the proposed model is verified by experiments. Experimental results manifest that the proposed model's performance is apparently improved compared with the traditional model, with the recognition accuracy up to 98.1 % in the Mnist dataset. Meanwhile, the recognition accuracy is enhanced, and the running time of the model is reduced to 640.4s. After the system simulation experiment, it can be found that the designed system can complete the previous requirement analysis of the system function and verify the feasibility and rationality of the proposed model and system. There are also many shortcomings. For one thing, there is no detailed simulation for the proposed process model, and the performance comparison only considers the identification accuracy and running time. More performance comparative analysis will be conducted in the subsequent exploration. For another is for the development of an educational management information system, its security and stability is the first consideration, and the two performance has higher requirements, not carelessness. The system can better serve users and teachers only by solving the problem of security and stability. After that, the system's security will be analyzed to ensure its proper operation.

Data availability

All data generated or analyzed during this study are included in this published article [and its supplementary information files].

CRediT authorship contribution statement

Xudong Liu: Writing – review & editing, Writing – original draft, Visualization, Validation, Project administration, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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