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A Method for Digitizing Talent Profiles in Higher Education Institutions Based on Image Recognition Algorithms

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Abstract As the construction of talent teams in higher education institutions enters a new era, their digital transformation efforts have also faced urgent demands and valuable opportunities for development. This paper utilizes deep learning technologies such as image recognition, speech recognition, and text mining to construct a comprehensive digital visualization model framework tailored to the talent profiles of higher education institutions. The practical performance and efficiency of the proposed algorithm are validated using the CIFAR-10 and ImageNet datasets. The results show that compared to traditional algorithms, the deep learning image recognition algorithm proposed in this paper achieves higher recognition accuracy and shorter training time, not only improving computational efficiency but also reducing model storage requirements. Through visualization analysis, significant differences (P=0.001) were observed in the cultivation of six key competencies—professional ethics, cultural adaptation, teaching practice, scientific research, student guidance, and social service—among faculty members at University A before and after the implementation of the model.

Index Terms deep learning, image recognition, talent profiling visualization

I. Introduction

A talent profile refers to the comprehensive evaluation, description, and summary of talent through various means, thereby forming a comprehensive, accurate, and in-depth information archive about the talent [1], [2]. In higher education institutions, talent profiles are divided into faculty talent profiles and student talent profiles [3]. Building a high-quality faculty talent pool of appropriate size, optimized structure, and reasonable distribution is of critical importance to the future development of higher education institutions [4], [5]. The student talent portrait will be "student-oriented", fully displaying the personality characteristics, psychological needs, study habits, career tendencies, hobbies, knowledge and skills of college students at different stages, which can provide empirical data support for colleges and universities to adjust and update talent training programs in a timely manner [6]-[9].

In the digital age, the digitization of talent profiling provides a scientific basis for the recruitment, cultivation, evaluation, and career development of high-level talent in universities, and has become a key factor in enhancing the core competitiveness of universities [10]-[12]. The digitization of university talent profiling can help managers gain a more accurate understanding of faculty members' capabilities, expertise, teaching styles, research interests, and development needs, thereby optimizing resource allocation and improving teaching quality and research standards [13]-[15]. This digital management approach has gained widespread recognition in the academic community [16]. At the same time, the digitalization of talent profiles can provide data analysis and guidance for students' individual learning growth and career development. Additionally, based on individual digital profiles, cluster analysis methods can be used to create group digital profiles of university students [17]-[20]. In the process of university education governance and improvement, analyzing the current learning and development patterns of university students, predicting professional employment trends, and providing data services for the Ministry of Education to formulate overall talent cultivation and development plans are essential [21], [22]. Image recognition algorithms, as a type of computer vision technology, analyze and process images to identify objects or features within them and make judgments based on specific classification or recognition rules [23]-[25]. In the field of constructing digital talent profiles in higher education, image recognition algorithms combine visual data analysis with multimodal information to achieve intelligent talent assessment methods, which are widely applied in the construction of digital talent profiles in higher education [26]-[28].

“Talent profiling” represents the integration of “user profiling” technology with talent optimization management. In the process of university human resource management and talent cultivation, precise service and management of talent have become increasingly important, holding significant implications for university human resource management, teacher career development, and talent cultivation. Literature [29] emphasizes the importance of constructing a talent profiling platform for universities, which primarily enables universities to monitor students' development dynamics in real time, implement targeted strategies, and provide accurate guidance for teaching, thereby putting the student-centered teaching philosophy into practice. Literature [30] examines a profiling system for sponsored students, which consists of a student data integration platform and a “five-dimensional” profiling model. It aims to support universities in promoting personalized education plans, enhancing students' comprehensive abilities, and improving collaborative sponsorship and educational capabilities within higher education institutions. Literature [31] proposes an integrated optimization clustering framework to accurately classify students. Through experiments, it demonstrates that this method can adapt to various types of data with distinct features, providing references for personalized education, educational equity, and talent cultivation in higher education institutions. Literature [32] examines student behavior shaping in higher education marketing education, constructing a student profiling system to concretize students' marketing capabilities, facilitating the provision of personalized, precise educational resources and methods based on students' label characteristics. Literature [33] discusses the demand characteristics of talent profiling in recruitment data, aiming to transform the traditional “empirical” teaching model and promote “data-driven” precision cultivation reforms. It constructs a talent profiling model from basic qualities and tool skills, analyzing talent demand characteristics. Literature [34] utilizes big data technology to construct a precision academic guidance model for college students based on big data profiling analysis. By collecting resource data and establishing a portrait tagging system, it provides references for accurately guiding students' academic development and supports the high-quality development of talent cultivation in higher education institutions. Literature [35] employs advanced data analysis techniques to analyze the process of constructing student portraits and explores their application in personalized teaching. The analysis results indicate that portraits have a positive impact on early warning and learning path design, providing technical support for implementing precision education. Literature [36] explains the background and significance of a student capability profiling system based on big data, describes the system's construction and presentation process, and reveals that the student profiling system plays an important role in improving students' learning efficiency and effectiveness. Literature [37] established a “one platform, three dimensions, five rings” model based on the “Yunnan Campus” data application platform, forming a diverse evaluation system in terms of subject, content, and methods, as well as a three-dimensional, scientific, and precise evaluation system for student growth. Literature [38] introduces the digital profile of the comprehensive quality evaluation platform, noting that it is generated from daily evaluation data provided by teachers, students, and parents, comprehensively presenting students' dynamic growth. This effectively breaks free from the framework of traditional paper-based evaluations and enables real-time understanding of students' strengths and weaknesses.

Addressing the limitations of traditional image recognition algorithms, such as high computational complexity, significant resource consumption, and room for improvement in recognition accuracy, this study proposes an optimized deep learning image recognition algorithm, optimizing aspects such as feature extraction, model results, and training methods. Based on this, this paper primarily constructs a digital visualization model framework for university talent profiling. By collecting behavioral data such as board writing, speech, and body language, as well as emotional data such as facial expressions from university talent, this study employs deep learning image recognition, speech recognition, natural language processing, body detection, and text mining technologies, combined with data visualization, to convert this information into digital portraits.

II. Research on digital portraits of university talent

II. A. Relevant Theoretical Foundations

The concept of university talent profiling originated from user profiling, which was first proposed by Cooper, the father of interaction design. He believed that user profiling is a virtual user model constructed based on a large amount of real data, and was initially mainly applied in fields such as e-commerce, libraries, healthcare, tourism, and social media. University faculty profiling is an important branch of user profiling research. In recent years, with the application of new technologies such as big data and artificial intelligence, research on describing university faculty characteristics based on user profiling has gradually emerged, such as researcher profiling to extract faculty research characteristics, teaching behavior profiling to reflect faculty teaching behavior characteristics, and learner profiling to reflect faculty learning behavior characteristics. These research findings focus on describing single-dimensional characteristics of faculty, primarily concentrating on the construction and implementation of label models. From the perspective of faculty professional development, university faculty members are comprehensive talents integrating teaching, research, service, and management. Therefore, faculty characteristics should be depicted from multiple dimensions to create a more comprehensive faculty profile. This study proposes a method for constructing a university talent profiling platform under multi-source, multi-dimensional data. On one hand, it collects faculty big data to establish a multi-level, multi-dimensional tagging system for the university talent profiling platform, enriching the dimensions displayed on the profiling platform. On the other hand, it combines data mining technology with teacher big data to focus on analyzing the key technologies of label modeling in the construction process. Finally, it explores the application of the university talent profiling platform in precise university management through case studies, providing references for achieving precise management of university faculty teams [39].

II. B.Visualization of talent profiles

The results of the talent capability profiling for higher education institutions can be presented in a multi-dimensional manner using data visualization techniques to showcase the characteristics and levels of teachers' capabilities. This approach must ensure that the visualized results are highly interpretable while also enabling relevant stakeholders to understand the output, thereby supporting the making of scientifically sound and reasonable educational decisions. Through the intelligent recording system, behavioral data such as board writing, speech, and body language generated in the teaching scenario, as well as emotional data such as facial expressions, are recorded and collected throughout the process. These data are then analyzed using embedded data analysis technologies (image recognition technology, speech recognition technology, text mining technology) for skill assessment, as shown in Figure 1.

(1) Data visualization

Data visualization refers to the process of converting complex data into simple, accurate graphical representations to enhance users' perceptual characteristics, help users deconstruct complex data information, and convey simple knowledge explanations. The data visualization module is the terminal interface that interacts with users, and its presentation directly influences teachers' and educational administrators' intuitive perceptions, their comprehensive and accurate understanding of assessment results, and indirectly impacts the scientific nature of educational decision-making. Data visualization has three basic characteristics: first, it is easy to read in form, and the visualized explanatory content is easy to understand and accept; second, it has explanatory accuracy in content description, often using quantitative descriptions rather than qualitative descriptions, with the former being superior to the latter in terms of explanatory accuracy [40].

(2) Types of visualization for portraits

The core activities of data visualization include selecting data attributes, choosing visualization templates, and establishing visualization mapping standards. The selection of visualization methods depends on the data attributes being described, and their suitability affects the interpretability of the information being conveyed. Therefore, this study will explore visualization methods for portraits based on four different attributes: behavior, social interaction, cognition, and emotion.

1) Visualization of Teacher Behavior Profiles

Chalkboard writing skills, verbal behavior, body language, and eye movement behavior are important external manifestations of a teacher's capabilities. Teacher behavior profiles visually reflect a teacher's ability to handle teaching tasks by depicting the status and changes in their behavior. The visualization of teacher behavior includes the visualization of behavior frequency, time-based behavior sequences, and space-based behavior trajectories.

2) Visualization of teacher social interaction profiles

With the deepening application of technologies such as the internet and social networks, social network information generated by teachers in the process of nurturing students and self-development can be recorded. In practice, social networks are commonly used to visualize data such as interaction direction, frequency, centrality, and density. Social networks offer intuitive visual effects and can handle large-scale observational dynamic attribute data sets, such as visualizing teachers' real-time interactions in online communities. By analyzing the topological structure features of social networks between teachers, students, parents, and colleagues, social interaction profiles can be generated to reflect teachers' communication and collaboration abilities.

3) Visualization of teachers' knowledge profiles

To be competent in teaching and education, teachers must possess a certain foundation of educational and subject knowledge and continuously reconstruct their cognitive schemas. With the deepening of computer science research, concept maps, knowledge graphs, and cognitive maps have emerged as tools for visualizing the organizational structure of knowledge in the human brain, making them suitable for constructing teacher knowledge profiles. (1) Concept maps are used to illustrate the relationships between concepts, forming meaningful statements, and are suitable for visualizing teachers' understanding of minor knowledge points. (2) Knowledge graphs are similar to concept graphs but have simpler diagrams, making them easier to form large-scale semantic networks, such as visualizing the subject knowledge systems teachers master. (3) Cognitive graphs can be used to represent the causal reasoning processes or factor influence processes teachers undergo when solving problems or making decisions.

4) Visualization of teachers' emotional portraits

Emotions such as care, appreciation, and anticipation play an important role in teachers' abilities. Visualizing teachers' emotions can be used to explore their emotional experiences and changes regarding professional identity, professional happiness, caring for students, and research enthusiasm. Visualization techniques for teachers' emotional portraits primarily include geometric diagram techniques and the Wheel of Emotions technique. Geometric diagrams such as bar charts, scatter plots, river diagrams, and rose diagrams are commonly used to display the distribution of teachers' emotional values across different time periods or scenarios. The Emotional Wheel technique is a visualization method. The Emotional Wheel consists of eight basic emotions, each corresponding to three intensity levels. This unique Emotional Wheel model can illustrate the complexity and multifaceted nature of teachers' emotions under specific conditions. The aforementioned visualization methods all focus on how to visualize the process-oriented changes in teachers.

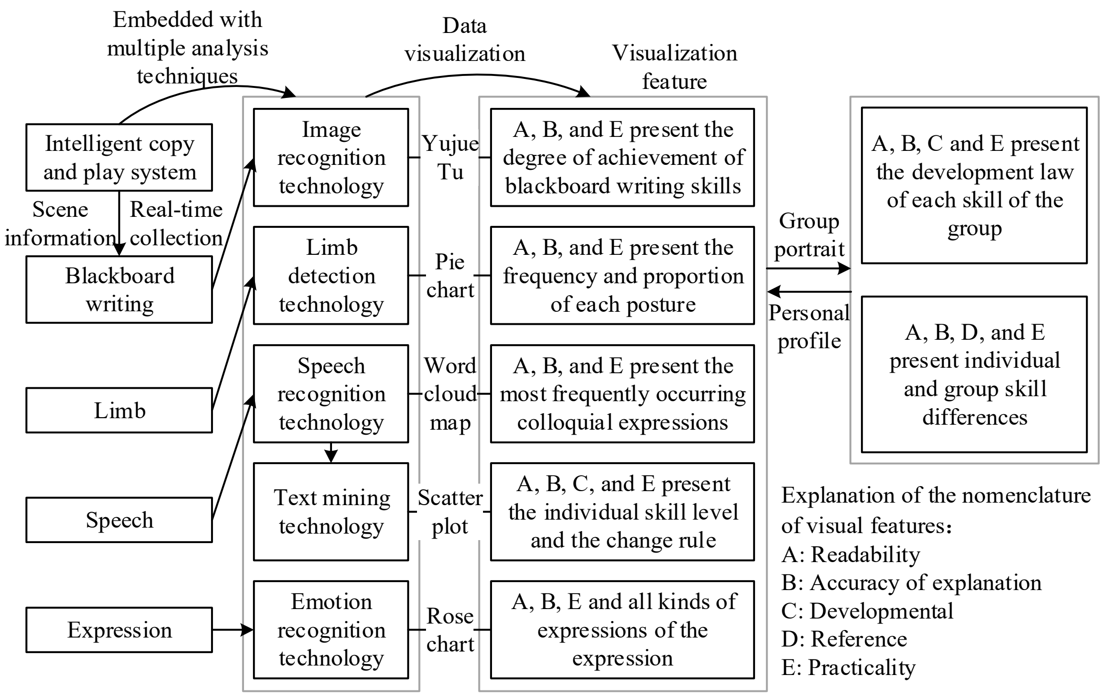


Figure 1: Visual presentation type of portrait results

III. Deep learning image recognition algorithms

Deep learning, particularly convolutional neural networks (CNNs), has become the mainstream method in the field of image recognition. CNNs automatically learn hierarchical feature representations of images through the stacking of convolutional layers, pooling layers, and fully connected layers, effectively capturing both local and global information in images. Compared to traditional machine learning methods, deep learning models offer the advantage of end-to-end learning, eliminating the need for manually designed feature extractors and significantly improving recognition accuracy. In recent years, deep learning models have achieved a series of breakthroughs in the field of image recognition [41].

III. A. Optimization based on feature extraction

The convolution layer performs convolution operations on the input feature map using the convolution kernel to extract local features from the image. Its basic mathematical expression is:

$$y = \sigma(w \times x + b) \tag{1}$$

In the equation, σ represents the activation function (e.g., ReLU), w represents the convolution kernel weights, x represents the input feature map, and b represents the bias term. The multi-scale convolution kernel combination strategy can simultaneously capture local details and global information in an image. In the shallow layers of the network, smaller convolution kernels (3×3) are used to extract local features such as texture and edges from the image; in the deep layers of the network, larger convolution kernels (5×5, 7×7) are used to capture semantic information from the image.

The introduction of the spatial pyramid pooling module further enhances feature extraction capabilities:

$$F = [P1(x), P2(x), ..., Pn(x)] \tag{2}$$

In the equation, P_i represents pooling operations at different scales, capturing features from different receptive fields through multi-scale pooling. In the feature fusion stage, the expression for the weighted fusion mechanism is:

$$O = \sum(\alpha_i \times F_i) \tag{3}$$

In the formula, α_i represents the weight coefficient of the i th feature map, which is automatically learned through the backpropagation algorithm.

VGGNet achieves feature extraction with a large receptive field by stacking small convolution kernels, while GoogleNet's Inception module further enhances feature diversity through parallel multi-scale convolution. These innovations provide important references for feature extraction optimization in deep learning models.

III. B. Optimization based on model structure

Residual learning introduces skip connections, directly adding the inputs of the network layers to the outputs, making it easier for the network to learn identity mappings. The mathematical expression is:

$$H(x) = F(x) + x \tag{4}$$

In the equation, $F(x)$ represents the residual mapping, and x represents the input information. During the gradient backpropagation process, skip connections create shortcuts for gradient flow:

$$\partial L / \partial x = \partial L / \partial H \cdot (\partial F / \partial x + 1) \tag{5}$$

Due to the existence of 1, even if $\partial F / \partial x$ approaches 0, the gradient can still propagate effectively, thereby avoiding gradient vanishing.

The multi-branch structure adopts parallel convolution, with different branches using different-sized convolution kernels (1×1, 3×3, 5×5) or different expansion rates to expand the receptive field and capture feature information at different scales. The output features are fused through a concat operation:

$$Y = Concat[F1(x), F2(x), ..., Fn(x)] \tag{6}$$

ResNet breaks through the barrier of network depth to 152 layers through this structural innovation. RiR enhances feature reuse through nested residual structures, while Wide ResNet improves computational efficiency while maintaining depth advantages by increasing the number of channels to enhance model capacity.

III. C. Optimization based on training methods

To address the issues of accuracy fluctuations and convergence speed during the training process of deep learning image recognition models, we designed training method optimization strategies. We constructed an improved adaptive gradient update mechanism and introduced a momentum term to achieve stable parameter updates:

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t \tag{7}$$

In the equation, g_t is the current gradient, and β_1 is the momentum decay rate. This mechanism reduces parameter update oscillations by accumulating historical gradient information. For feature learning at different network levels, a variance-adaptive learning rate adjustment is designed:

$$v_t = B_2 v_{t-1} + (1 - B_2) g_t^2 \tag{8}$$

In the equation, β_2 is the control variance term update rate, which enables the learning process to adaptively adjust according to gradient changes. In the parameter update stage, momentum and variance terms are combined to achieve stable and efficient weight optimization:

$$\theta_t = \theta_{t-1} - \eta \cdot m_t / \sqrt{v_t + \varepsilon} \tag{9}$$

In the equation, η is the base learning rate, and ε is the numerical stability factor. Shallow networks use a smaller learning rate to maintain the stability of feature extraction, while deep networks use a larger learning rate to accelerate convergence. A warm-up strategy is introduced into the training process to gradually increase the learning rate and avoid violent oscillations in the early stages of training. In the later fine-tuning stage, a periodic learning rate adjustment mechanism is combined to achieve precise optimization of model performance. This training optimization scheme improves training efficiency while effectively ensuring the convergence stability and generalization ability of the model.

IV. Experiments and analysis

IV. A. Dataset

To comprehensively validate the practical performance and efficiency of the proposed algorithm, we carefully selected two publicly available image datasets that are highly influential in both academia and industry for detailed experimental analysis: CIFAR-10 and ImageNet. The CIFAR-10 dataset consists of 70,000 32×32-pixel color images divided into 10 categories, with each category containing 7,000 images, of which 6,000 are used for training and 1,000 for testing. The ImageNet dataset, on the other hand, is a massive visual database containing over 15 million images, categorized into 22,000 classes. It is one of the largest image recognition datasets currently available and is widely used to evaluate the performance of computer vision algorithms.

IV. B. Experimental Environment

All experiments were conducted in an advanced hardware and software environment with the following configuration to ensure the accuracy and reproducibility of the experimental results. The CPU is an Intel i7-10700K processor with a clock speed of up to 3.84 GHz, providing powerful data processing capabilities. The GPU is an NVIDIA GeForce RTX 3080 graphics card with 10 GB of VRAM, providing the necessary computational acceleration for deep learning model training. The memory is 64 GB DDR4, ensuring system stability and responsiveness when processing large-scale datasets. The operating system is Ubuntu 18.04 LTS, a stable and widely used Linux distribution, providing an excellent development environment for deep learning research; the programming language is Python 3.8, which has become the preferred programming language in the field of deep learning due to its rich library support and concise syntax. The deep learning framework is TensorFlow 2.4, an open-source machine learning framework renowned in the deep learning community for its flexibility and powerful functionality. Through the above detailed experimental environment configuration, we have established a fair and efficient testing environment for the proposed deep learning image recognition algorithm to accurately evaluate its performance in practical applications.

IV. C. Experimental Results

IV. C. 1) Recognition accuracy rate

To thoroughly investigate the performance advantages of the proposed optimized deep learning image recognition algorithm in image recognition tasks, we conducted a comprehensive comparative experiment with traditional deep learning image recognition algorithms. The experimental results were analyzed in detail on two representative datasets, CIFAR-10 and ImageNet. The following is an in-depth analysis of the experimental results. As shown in Table 1, the two algorithms demonstrate their recognition accuracy on different datasets. The optimized algorithm proposed in this paper achieves significant improvements in accuracy on both the CIFAR-10 and ImageNet datasets, indicating the superiority of the optimized algorithm in image feature extraction and classification capabilities.

Table 1: Recognition accuracy

Data set	Traditional algorithm accuracy	This algorithm
CIFAR-10	92.8	95.8
ImageNet	72.2	74.9

IV. C. 2) Training time

The training times of the two algorithms on the CIFAR-10 dataset are shown in Figure 2. By introducing deep convolutional layers, the optimized algorithm significantly reduces training time while maintaining high recognition accuracy, which is of great significance for improving efficiency in practical applications.

The differences between the two algorithms in terms of model size and computational complexity are shown in Table 2. The optimized algorithm effectively reduces the number of model parameters and computational complexity by introducing deep convolutional layers, which not only improves computational efficiency but also reduces the storage requirements of the model.

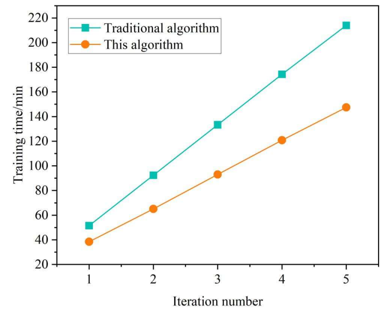


Figure 2: Training time contrast

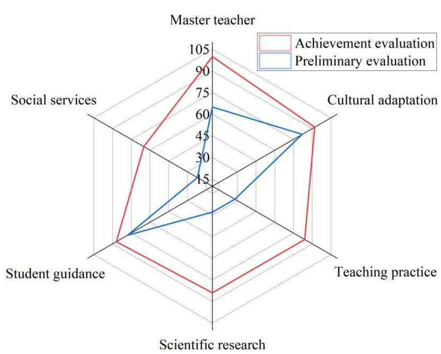
Table 2: Parameters and calculation

Algorithm	Parameter quantity/ per million	Calculate over / million times
Traditional algorithm	23.8	5.3
This algorithm	8.4	2.2

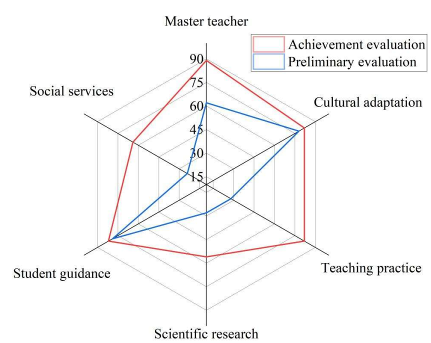
V. Examples of digital talent profiling in higher education institutions

V. A. Data Sources

In line with the trends toward the intrinsic development of higher education and the digital transformation of higher education in China, applied universities play a significant role in the higher education sector. Compared to traditional research-oriented universities, such institutions demonstrate higher market sensitivity. University A was established in Sichuan Province with approval from the Ministry of Education of China. It was founded by D Group, a leading IT solutions and services provider in China, and is an innovative applied undergraduate institution with a faculty comprising dual-qualified teachers and professionals. The average number of students on campus over the past five years has been approximately 13,500. The institution focuses on the integrated development model of "IT+Management" and "IT+Business" new engineering and new liberal arts disciplines, building distinctive disciplinary clusters. It is committed to cultivating application-oriented senior specialized talents with a foundation in information and business technology, oriented toward modern enterprise management and operational solutions, and characterized by enterprise management information systems and business operations. Due to its historical and industry background, it has its own standards and specifications in the cultivation of application-oriented talents in management-related disciplines. Therefore, this study selected University A and used a radar chart analysis to examine the differences in the six competency areas—professional ethics, cultural adaptation, teaching practice, scientific research, student guidance, and social services—before and after a six-month training program for newly hired faculty members during the fall semester of the 2023–2024 academic year. The aim was to explore the effectiveness of university talent development based on a talent profile visualization platform. The descriptive statistical results for the six competency areas are shown in Figure 3.



(a) Prediction of development expectations and results



(b) The beginning of the culture and the end of the culture

Figure 3: The development of the pre-maturity and final capacity of the training

V. B. Data Description

University A hired 45 new teachers for the fall semester of the 2023-2024 academic year. After excluding teachers who left during the six-month training period, 39 new teachers were evaluated on their professional ethics, cultural adaptation, teaching practice, scientific research, student guidance, and social service skills before and after training. SPSS 26.0 was used to compare and analyze the specific data characteristics of the new teachers' skills during the two observation periods. Since the sample size was less than 50, the Shapiro-Wilk test was used to test for normality.

The results of the talent profile visualization data description are shown in Table 3. The sample data sets for the six competency areas in both observation periods did not show significant differences ($p > 0.05$), and the data distribution was approximately normal. The difference between the median and mean of the six competency and ability metrics in the first observation period was smaller than that in the second observation period, indicating that the latter was more influenced by outliers. Within the same observation period, the means of the six competency and ability metrics were close, while the means across different observation periods showed significant differences. Additionally, the standard deviation decreased in the latter observation period, indicating that the latter means were more representative and the dataset exhibited greater stability. In summary, there were significant differences between the variables.

Table 3: 6 ability data descriptive statistics

Variable	Max	Min	Mean	Median	SD	S-W test	
						W	P
Stage1_ Master teacher	80	28	56.887	57	13.385	0.985	0.487
Stage1_ cultural adaptation	87	22	57396	58	15.589	0.962	0.09
Stage1_ teaching practice	78	36	55.079	56	10.120	0.994	0.811
Stage1_ scientific research	79	20	42.855	46	14.925	0.968	0.302
Stage1_ student guidance	84	24	48.056	48	14.315	0.962	0.184
Stage1_ social services	60	32	45.147	47	6.385	0.958	0.112
Stage2_ Master teacher	94	62	80.114	84	6.822	0.974	0.584
Stage2_ cultural adaptation	100	70	85.745	86	7.384	0.958	0.148
Stage2_ teaching practice	93	72	81.022	81	5.224	0.968	0.256
Stage2_ scientific research	86	56	70.078	73	7.118	0.985	0.457
Stage2_ student guidance	92	65	77.184	79	6.214	0.950	0.080
Stage2_ social services	84	52	68.952	74	7.779	0.966	0.225

To observe the trends in the development of the quality and capabilities of newly hired teachers at University A during the fall semester of the 2023-2024 academic year before and after training, a paired sample t-test was further used to test the paired differences in the six quality and capability items of the sample subjects at the two observation periods, as shown in Table 4. All six paired competency data points exhibited statistical significance at the 0.01 level (t-values ranging from -12.530 to -22.356, $p = 0.001$). The effect sizes were large (Cohen's $d > 0.8$), with the pre-training average values for all competencies significantly lower than the post-training average values. In particular, the competencies of student guidance and cultural adaptation exhibited significant differences.

Table 4: Six ability matching sample test results

.		Mean	95%CI	df	t	p	Cohen's d value
Pair1	Stage1_ Master teacher Stage2_ Master teacher	-23.25	-25.541~-20.933	40	-20.407	0.001**	3.268
Pair2	Stage1_ cultural adaptation Stage2_ cultural adaptation	-28.42	-32.952~-23.778	40	-12.530	0.001**	2.008
Pair3	Stage1_ teaching practice Stage2_ teaching practice	-25.14	-27.342~-22.514	40	-20.886	0.001**	3.352
Pair4	Stage1_ scientific research Stage2_ scientific research	-27.38	-30.068~-24.400	40	-20.48	0.001**	3.119
Pair5	Stage1_ student guidance Stage2_ student guidance	-30.02	-32.763~-25.517	40	-22.356	0.001**	2.8
Pair6	Stage1_ social services Stage2_ social services	-25	-26.178~-21.833	40	6.714	0.001**	3.584

VI. Conclusion

This paper utilizes optimized deep learning image recognition technology, speech recognition technology, text mining technology, and limb detection technology to construct a comprehensive digital visualization model framework for talent profiling in higher education institutions. Through comparative experiments, the actual performance and efficiency of the proposed algorithm are comprehensively validated. Analysis shows that deep learning image recognition algorithms can maintain high recognition accuracy while reducing training time. The introduction of deep convolutional layers effectively improves computational efficiency. Using the visualization model proposed in this paper, it is possible to describe the differences in six key competencies of faculty members at University A: professional ethics, cultural adaptation, teaching practice, scientific research, student guidance, and social service.

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