The Application of Multimedia and Deep Learning in the Integration of Professional and Innovative Education in Colleges

Shilin Xu, School of Accounting, Wuchang Institute of Technology, China*

ABSTRACT

In this paper, the authors study the assessment of professional practice courses in the integrated education of specialization and innovation, and use the multimedia and deep learning technology to complete the action recognition of students in practice courses. Firstly, the skeletal features are extracted from multimedia video data by Openpose algorithm, which is used for subsequent classification while ensuring privacy; then the LSTM method is used to recognize typical motions in student practice, and the average recognition result exceeds 89%; finally, practical application tests are conducted for laboratory and office scenes, and the results illustrate that the proposed framework performs well in the tests with recognition rate exceeding 80%. The algorithm framework provides a new idea for the curriculum setting and evaluation method of professional practice education, and gives data guarantee for their integration and innovation education.

KEYWORDS

Deep Learning, LSTM, Multimedia Teaching, Professional and Creative Education Fusion

INTRODUCTION

The role of professional education is becoming increasingly prominent within our rapidly developing societies. Due to an increasing demand for innovative talent, there is a need to promote high-quality professional development and enhancements in higher education. In this context, the integration of professional education and innovative education has become a first choice for many schools (Jarvis & Wilson, 2004). Vocational curriculum should be closely connected to professional development. This education should be distinct and flexible according to industrial needs, occupational standards, and production processes (Orishev Burkhonov, 2021). It is also necessary to develop trends in science and technology to meet market demand. In doing so, we can better integrate and promote advanced innovative education and professional education (Morales & Suárez-Rocha, 2022). Figure 1 shows the main principles of the integration of professional and creative education (Ramírez-Montoya et al., 2021).

According to Figure 1, the current integration of professional and creative education considers professional education as a research theme. It completes the integration of specialization and innovation

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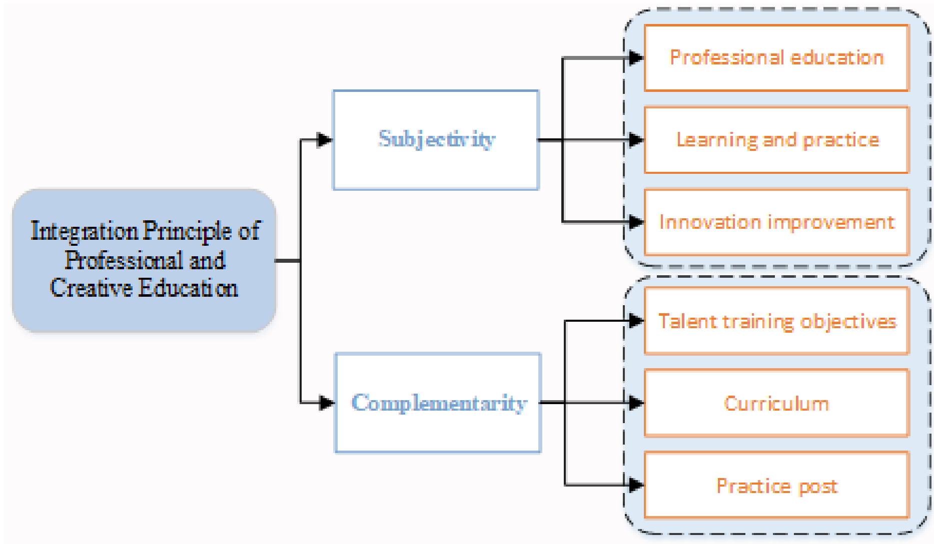
*Corresponding Author

Figure 1.
Principle of the integration of professional and creative education



in the new era by complementing it with innovation education, improving the quality of human resources (Wu, 2022). Therefore, a university's teaching and curriculum should stress the value of professional education with a focus on practical values.

In the process of continuous iteration of science and technology, teaching methods have undergone great change. The application of streaming media technology continues its development. Today, its interactive, real-time network multimedia teaching system that has become a powerful channel for teaching. The network multimedia system adopts a variety of advanced information technologies. For example, video technology provides a two-way interactive network multimedia teaching platform. The advantages of multimedia lectures can be fully utilized in course development and combined with the latest artificial intelligence to improve efficient talent training (Lu & Wu, 2022).

Innovation education continues to take shape after years of development. Thus, the integration of professional education into innovation education through intelligent means is a priority. Professional education is focused on putting knowledge from textbooks into practice and connecting it with one's life. The current educational process can be complicated by the type of practice, making it difficult to complete an assessment or its accurate integration with innovative education (Dovha et al., 2021). In today's world of highly developed multimedia teaching and artificial intelligence (AI), it is possible to use online multimedia data to gain an intelligent assessment of students' professional educational practices with the help of AI.

Deep learning techniques and powerful neural networks (NN) form a black box effect to complete the analysis of multimedia multimodal data. It can realize the task of identification, assessment, and analysis of students in such courses (Onan, 2021). The current multimedia-based education on innovative AI technologies within universities study how the use of wearable devices, video devices, and related assistive devices enhance professional education. In physical education, online course evaluation is based on AI multimedia technology and human motion capture technology. Psychological education efficiency is improved through the acquisition of multi-source physiological signals and the recognition of facial micro-expressions. In course evaluation, the intelligent analysis of final grades is realized through a high-precision NN approach that integrates usual performance and coursework (Wollowski et al., 2016).

AI also provides opportunities in multimedia teaching, offering more intelligent references for the design and evaluation of courses. In practice education, it is important to guarantee both the practical effect and privacy. Thus, information about the appearance and morphology of the task must be hidden when evaluating labor and operations. Skeletal feature extraction, therefore, is based on the OpenPose framework in deep learning.

This article studies student practice in professional education in the context of professional and creative integration. Typical motions in practice are identified using web-based multimedia video technology. It aims to improve intelligent assessment methods in practice courses, as well as capture the dynamics of student practice. Overall, it provides intelligent ideas for professional and creative integration. The article's contributions include the following:

- The OpenPose method completes the skeletal framework feature extraction for typical motions in the practice process. It provides data support for high-precision classification.
- Typical action classification is based on the long short-term memory (LSTM) model with OpenPose skeleton features. It has an average recognition rate of more than 89%, demonstrating strong recognition results.
- A practical test is conducted after completion of the model training and optimization. The test results of office and laboratory scenes show that the model could complete the motion recognition in the practical course with high accuracy. The recognition accuracy of all kinds of motions exceeds 80%.

The remainder of the study is organized as follows. Section 2 introduces related works for multimedia teaching and deep learning application. Section 3 introduces methods. Section 4 carries out an experiment, resulting in an analysis of the practice course and discussion of the model application. Section 5 reviews the results.

RELATED WORKS

Multimedia Application in Teaching

With the development of information technology, multimedia teaching has moved away from the simple PPT mode. It has entered a diversified research stage with more advanced information technology. The application of multimedia technology in teaching can be summarized as network development, intelligent development, and virtual reality development. Among them, network word development is realized through online teaching. This became the main method of teaching during the COVID-19 pandemic. Online course design with video, pictures, and interactive programs became the main development of multimedia teaching networks (Black, 1992).

Intelligent multimedia teaching aims to achieve the intelligence of multimedia software (Tashpulatovich, 2021). By introducing AI, multimedia teaching becomes more vivid. Obscure mathematical and physical principles are explained. In addition, content is evaluated by intelligent means. The combination of these intelligent teaching aids and multimedia technologies improve the efficiency of a course (Kumar et al., 2021).

Today, virtual reality and somatosensory technologies are more mature. They map human movement into multimedia educational content, enhancing the sense of immersion. Students are then able to acquire useful knowledge in an efficient manner (Martins & Gresse Von Wngenheim, 2022).

It can be found that the scope of multimedia teaching has expanded through physical education and instrument operation training or teaching through multimedia means. Overall, these tools have enhanced students' experiences. While virtual reality equipment is expensive and equipment operation is complicated, research is focusing on ways to extend the scope of multimedia applications through intelligent means (Wu, 2021).

Based on intelligent multimedia teaching methods, there are mature precedents for application in physical education in colleges (Lian, 2022). Combining the advantages of existing technologies, tightening the focus on professional education in specialized education, and enhancing intelligent teaching and assessment of practice are important directions for development.

Deep Learning for Human Motion Recognition

Students' practical behaviors need to be accurately analyzed in the process of professional education. Intelligent multimedia applications should use in-depth learning technologies to realize motion recognition in the teaching process. Regarding vision sensor-based research, there are many branches in the development of vision sensor-based research due to the sensors and processing methods involved. Kamthe and Patil (2018) established a model for human behavior recognition based on video streams captured by surveillance systems. The established model was used to achieve monitoring and recognition of human behavior. Park et al. (2018) obtained depth imaging information of the monitored target based on RGB-D depth camera technology. This technology obtains deeper human behavior information than traditional cameras and provides more information input for model building.

In recent years, with the improvement of computing power, the research on human motion recognition based on video information technology has developed rapidly. Park and Kim (2019) considered the influence of the external environment on human behavior recognition. They conducted an experimental study in a low-light environment to propose a three-dimensional (3D) image motion recognition method based on a convolutional neural network (CNN). Arif et al. (2019) put forward a new framework for behavior recognition by fusing 3D-CNN and LSTM networks. The discriminative information in the video is first integrated by a deep 3D-CNN. Then, the integrated information is re-integrated with the next video frame to increase the training length by iterative methods, thus increasing the training and recognition accuracy. Hossain et al. (2020) learned the heterogeneous spatiotemporal cues of video motion recognition. They performed an in-depth study of feature maps, focusing on extracting features with highly discriminative rows.

The development of deep learning technology has improved the accuracy and speed of human movement recognition. In the specialized education scenario, both innovative teaching and professional education are more often carried out through student practice.

This article adopts video data to identify students' motions under the practical courses in specialized innovation teaching. It refers to the advantages of current technologies in sports multimedia teaching and uses video data in college multimedia data to realize the intelligent evaluation of students' performance in such courses.

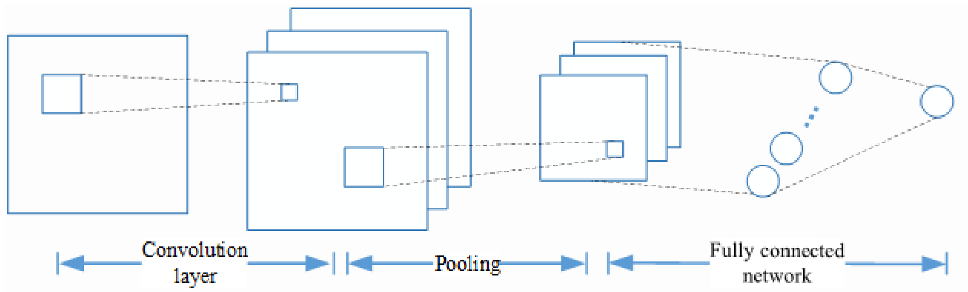
DEEP NN FOR MOTION RECOGNITION

CNN and Video Processing

CNN can effectively extract two-dimensional images with high-level data features. This is a hot method for image data processing. This type of NN can reduce the use of memory, lower network parameters, and alleviate problems like overfitting. The flow of the CNN is shown in Figure 2 (Kattenborn et al., 2021).

In Figure 2, the CNN shows the detailed process of image processing, with convolution and pooling as the main functions. The convolution process refers to the computation of the inner product of the convolution kernel according to the specified convolution kernel and step size to achieve feature extraction. The pooling layer can reduce the dimensionality without changing the data or image features. After the convolution and pooling operations, the fully connected layer achieves the output of results. CNN features include:

Figure 2.
CNN framework



1. **Local Perception:** The image is chunked when performing image recognition. Each neuron does not have to connect to all pixel units. It must connect to the local image, which can synthesize global perception information at a higher level. This approach can significantly reduce connections between adjacent layers of the network without compromising accuracy.
2. **Weight Sharing:** Features at neighboring locations are smaller when extracting features from one image. Therefore, one parameter can be used instead of the surrounding similar parameters. Thus, parameters are shared with the surrounding neurons, which can greatly reduce the number of parameters.
3. **Radiation Invariance:** The translation, scaling, and rotation invariance of the CNN make it more efficient than traditional artificial NNs. The basic principle of the OpenPose framework in this article is the CNN.

OpenPose for Skeleton Extraction

The OpenPose joint point detection algorithm is proposed by the Computational Research Laboratory at Carnegie Mellon University. The framework allows a real-time estimation of the pose of each human limb in a multi-person scenario. The framework of this detection algorithm is constructed by a confidence algorithm and local affinity algorithm. Unlike AlphaPose, OpenPose performs key point detection from the bottom up. The recognition speed does not decrease as the number of people in the recognized image increases (Lin et al., 2022).

The OpenPose model consists of two parallel CNN. In these two branches, one of the CNN is responsible for locating the human joint point S. The other CNN (L) is responsible for detecting the affinity of the limb. OpenPose first passes a convolutional network that extracts the underlying features. It passes the extracted features as input to these two parallel CNN before the next step. This is equivalent to two convolutional networks that extract the underlying part of the features extracted by two convolutional networks. It, in turn, saves a lot of performance. Its specific structure and implementation are shown in Figure 3:

$$S^t = \rho^t(F, S^{t-1}, L^{t-1}), \forall t \geq 2 \tag{1}$$

$$L^t = \varphi^t(F, S^{t-1}, L^{t-1}), \forall t \geq 2 \tag{2}$$

The two branch networks shown by OpenPose in Figure 3 are Eq. (1) and (2). F is the feature map. St is the confidence map of the nodes at the output of stage t. Lt is the affinity of nodes at the output time t (i.e., the weight coefficient). To ensure network convergence, the method uses the L2 loss function for both branches. Loss values of each stage are shown in Eq. (3) through Eq. (5) (Kim et al., 2021):

$$f_s^t = \sum_{i=1}^{J} \sum W(p) \cdot \left\| S_i^t(p) - S_i^*(p) \right\|_2^2 \tag{3}$$

$$f_L^t = \sum_{j=1}^{J} \sum W(p) \cdot \left\| L_j^t(p) - L_j^*(p) \right\|_2^2 \tag{4}$$

$$f = \sum_{t=1}^{T} (f_s^t + f_L^t) \tag{5}$$

After completing the training of function loss minimization, the angle of the joint can be calculated by the position of the pixel points in the image. This forms the corresponding features and completes the feature extraction of the skeletal structure. The calculation process of the skeletal joint is shown in Eq. (6) (D'Antonio et al., 2021):

$$\theta_n = \arccos \frac{r_{i,j}^1 \cdot r_{i,k}^1 + r_{i,j}^2 \cdot r_{i,k}^2}{\sqrt{r_{i,j}^{12} + r_{i,j}^{22}} + \sqrt{r_{i,k}^{12} + r_{i,k}^{22}}} \tag{6}$$

After the high-precision calculation of each joint angle, a skeletal sequence is formed to restore the motion features in the video. This provides data for subsequent feature calculation.

LSTM for Motion Recognition

LSTM NNs are excellent in processing time series data. They also have strong performance in building regression classification models (Liu et al., 2022). Both LSTM and RNN are chain structures. LSTM incorporates a gate structure to store the states of the cells. Due to the gate structure, the inverse error of the activation function can be passed down as the number of iterative layers increases. This avoids the long-term dependence problem. The chain of the LSTM is shown in Figure 4 (Lindemann et al., 2021).

The LSTM is a variation of the RNN, where the implicit layer incorporates forgetting gates, input gates, and output gates. It cannot only accept the output of the neurons in the previous layer, but also selectively retains useful information from historical moments through the gate structure. The forgetting gate which is used, as shown in Eq. (7), to select the state of the next computational unit by whether to forget (Shi et al., 2023):

Figure 3.
Construction of OpenPose

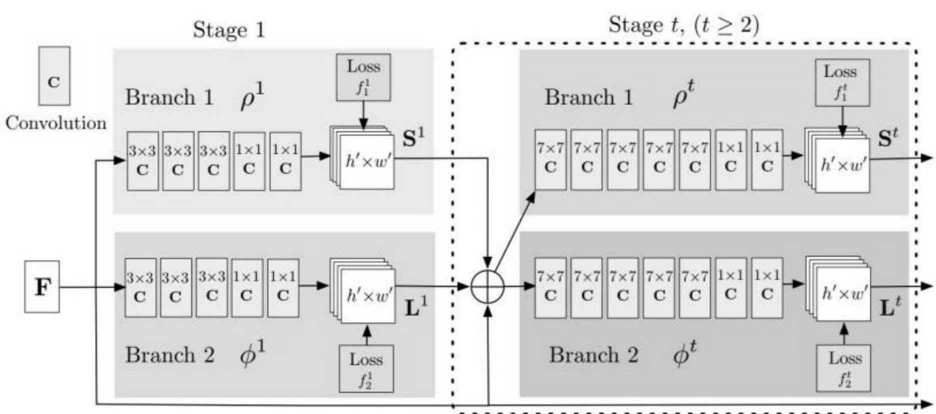
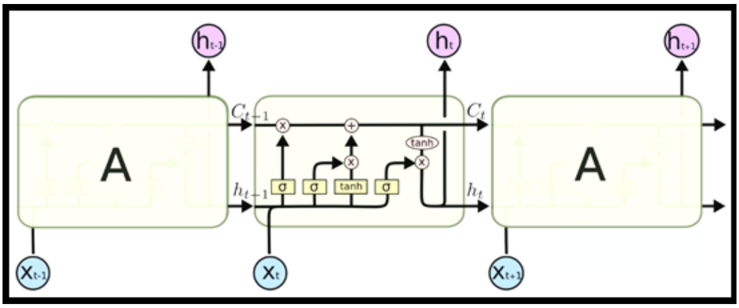


Figure 4.
Construction of the LSTM



$$C_t = f_t \times C_{t-1} + i_t \times \widetilde{C_t} \tag{7}$$
$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \tag{8}$$
$$h_t = o_t \times \tanh(C_t) \tag{9}$$

Finally, the output ht of the hidden node can be calculated by Eq. (8) and Eq. (9) to complete the input and prediction value calculation for the next time unit. The data in this article is mainly corresponding time series images after the feature extraction of skeletal joint data is completed. Thus, the data are classified by LSTM. The algorithmic framework proposed in this article is shown in Figure 5.

As seen in Figure 5, the framework can be used to realize the motion classification t. This shows the reproduction of movement related to the professional labor education of students in the process of specialized and integrated education. It provides technical support for subsequent curriculum innovation.

EXPERIMENT RESULTS AND ANALYSIS

Result for Motion Recognition

According to the algorithm framework in Figure 5, this article combines the current human body video motion dataset (https://github.com/woo-chia-wei/kinect-sequence-classification). Considering characteristics of practical courses, this article will identify common motions in daily life, learning, and practice. In the process of model building, the movements are divided into four categories: (1) walking; (2) sitting; (3) working with a computer; and (4) talking. The extracted skeletal framework is free from privacy risks. There is no privacy statement in this paper. Data from 20 people was collected, with each person learning and working in front of the camera. After completing the specified motion, the data collection was completed and data was trained. The classification results are shown in Figure 6.

Figure 5.
Framework for motion classification

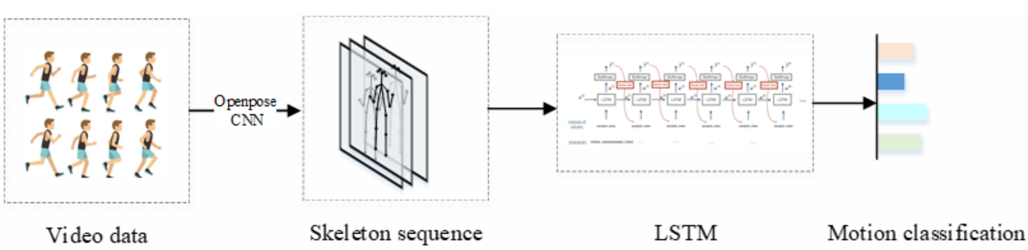


Figure 6.
Results for motion recognition

After comparison, it was found that the motion recognition framework had a good effect. The recognition results for the four types of data collected exceeded 85%, with an average recognition rate of 89.9%. Among the various types of motions, the recognition of walking was highest. This is because the location of the camera was accurately focused on the seat during data collection. The recognition rate of talking is lower because the judgment is mainly done by the distance between two people. There is a certain error. To better illustrate the accuracy of the proposed approach, other classification methods were tested on top of feature extraction based on the OpenPose skeleton framework.

Comparison Among Methods and Network Structure

The classification test included RNN, TCN, and NN methods whose network building structure was consistent with the LSTM structure. Only the unit features differed. The classification results of different methods are shown in Figure 7.

According to Figure 7, the LSTM method has a better effect due to the students' various activities throughout their participation in the experiment (with a certain degree of temporality). The TCN method, which has a stronger temporal function, has an average performance that may be due to its overly complex model, number of training sessions, and amount of data that failed to stimulate its performance.

Model Application in Different Scenes

After completing the training of the model, the practical application of the algorithm framework was tested according to the actual needs of the school based on location. The flow of the test is shown in Figure 8.

Figure 7.
Recognition results among methods

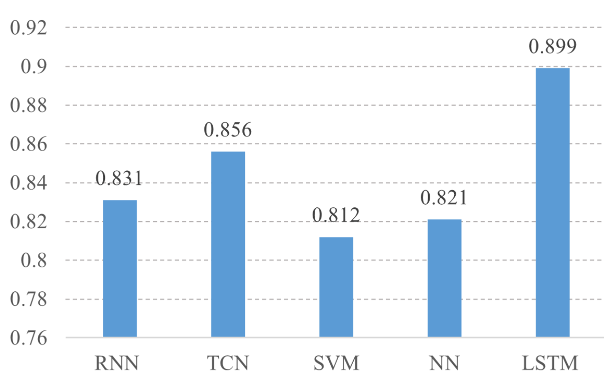
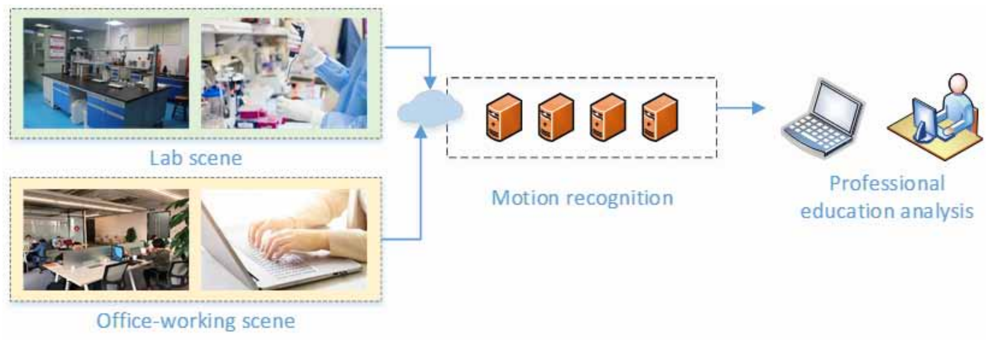


Figure 8.
Framework for application test



Experimental operations and indoor office scenarios common in current student practice were analyzed and tested following discussions with the university's academic and practical course departments. In the office work scenario, typical tasks were divided into four categories (i.e., keyboard, telephone, writing, and discussing). Discussing was divided according to the same criteria as talking in the model-building process. The other scenarios were divided according to the specified work order. The other scenarios are in the specified order of work. To better illustrate the characteristics of the LSTM classification method, RNN, NN, and TCN methods were selected for comparison for testing. The results of motion recognition in different scenes are shown in Figure 9 and Figure 10.

In the actual test, it can be found that the LSTM has higher classification accuracy than the traditional RNN and NN methods in both the city office scenario and laboratory experiment scenario. The performance of the TCN method in the laboratory scenario is not much different from the LSTM method. This is because the TCN has a strong time-volume memory and is slightly higher than the LSTM method in the operating instrument. However, the LSTM method performs slightly better than the TCN method in terms of overall accuracy, operation time, and model complexity. The recognition

Figure 9.
Recognition accuracy in office-working scene

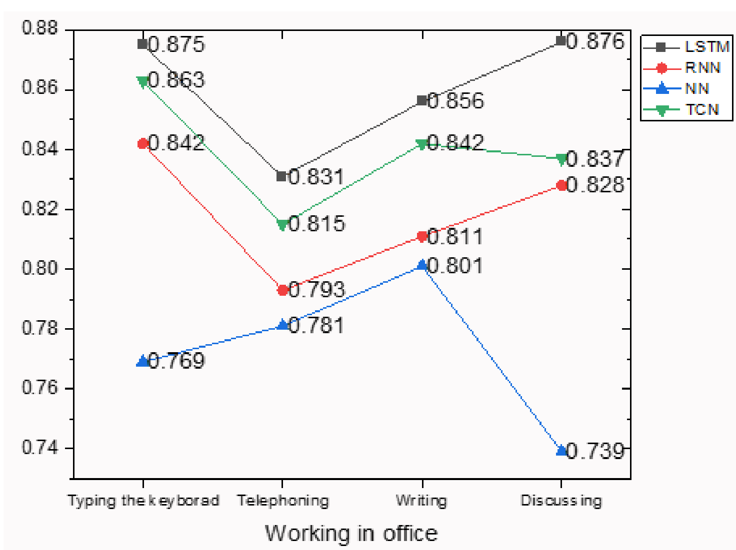
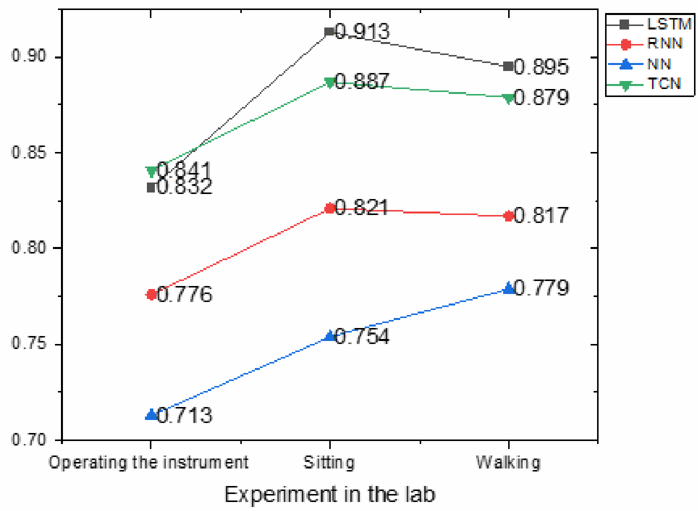


Figure 10.
Recognition accuracy in lab



results are lower than the accuracy of the classified motions when the model is built. In the actual test, the accuracy of skeletal feature extraction decreases due to human occlusion and the increase of objects. Therefore, it indirectly affects the recognition accuracy of the model. The lower accuracy recognition of the operating instrument in the laboratory scene is due to the instrument occlusion causing the motion to be divided into extended periods of sitting (which impacts recognition accuracy). Therefore, in the future practical application process, refinement of the various types of motions in practice and improvement of data acquisition methods will be the focus of practical application.

DISCUSSION

Computer technology, as well as its continuous application in teaching, is evolving. Its use to achieve efficient and convenient teaching is becoming an inevitable trend. In the context of the integration of professional and creative education, only classroom teaching faces challenges in achieving substantial change in the professional application of education for students.

Some people continue to explore the intelligent evaluation and analysis of offline practice based on multimedia data through emerging cloud computing, AI, and other technologies. Previous studies have used wearable hardware, Kinect depth cameras, or expensive VR devices to change methods within the teaching of physical education.

This article takes advantage of breakthroughs in AI-based pose estimation to achieve the estimation of human skeletal points in video images through the Openpose model. The human skeleton space is analyzed to eliminate the influence of same limb pinch features in similar movements, extract differential human posture features, and improve the differentiation ability of human posture features based on skeletal points for basic movements. In the process of building the developed framework, this article conducted classification performance tests based on classical NNs methods like LSTM and RNN. The results showed that the LSTM method has the best effect in the classification process. The work done by students in the practical process is more coherent and, like the labeled content, has a strong temporal order. Therefore, LSTM achieves the best results due to temporal memory.

The article's algorithmic framework for the offline practice process of professional education can identify typical motions in current work and experiments. It provides a data reference for students' practice courses in the process of professional education and assessing students' learning effects for their subsequent training plan updates.

It is also important to focus on the ideological education of students while promoting the integration of professional and creative education. As the recipients of education, it is essential to promote integration by revising students' understanding of innovation, awakening their awareness, and placing the concept into all teaching aspects of professional education. These efforts will cultivate students' innovative thinking, enhancing their sense of independent innovation and creativity. At the same time, colleges should pay attention to changing students' ideas by participating in innovation and entrepreneurship practice and training activities. Colleges should give full guidance and support, reasonably arrange training links and training time according to the talent training plan, ensure students' professional knowledge learning, increase opportunities for students to participate in innovation and practice, cultivate students' innovation thinking, and improve students' innovation ability. Teachers should guide students to explore innovation and practice throughout their region, participate in innovation competitions at all levels, and enhance their application ability.

CONCLUSION

This article investigates the curriculum and practical course evaluation in the process of training composite talents in professional education. It proposes a method for recognizing typical student movements in practical courses with the help of video surveillance data and deep learning technology. The method extracts motion skeletal features from video stream data using the OpenPose model of CNN. It then completes the human motion recognition by the LSTM method, with results showing that the LSTM method performs better than RNN and NN methods.

The test results in office and laboratory scenes show that the proposed framework is good at recognizing common motions in practice with high accuracy. Thus, it provides a practical reference for future specialized and integrated education.

Future research can expand the application scenarios and types of recognized motions. Studies can realize joint analysis with innovation education courses of specific universities. Thus, it will provide ideas for future education reform and talent training.

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CONFLICTS OF INTEREST

The study was conducted without any business or financial relationships that could be interpreted as a potential conflict of interest.

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