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Article

Biomechanical analysis of the effects of breathing techniques on dance performance and dancers' physiological state

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Abstract: This study aims to investigate the effects of different breathing techniques on the physiological state and expressive force of modern dance dancers. Here, a motion recognition model based on a Three-Dimensional Convolutional Neural Network (3D CNN) and a Transformer network is proposed to recognize dancers' movement performance under diverse breathing patterns. The study employs high-frequency motion sensors and physiological monitoring devices, combined with questionnaires and open datasets, to collect and analyze the dancers' heart rate, respiratory rate, muscle activation rate, and other data. The results show that under deep breathing conditions, the dancers' heart rate reaches 0.84, significantly higher than shallow breathing (0.46) and general breathing (0.61). Furthermore, the muscle activation rate is also remarkably increased to 0.95, better than general breathing (0.73) and shallow breathing (0.58). The model proposed in this study has excellent performance on motion recognition, with an accuracy of 96.89% at 0.5 dropout, remarkably exceeding other comparison models. The study concludes that deep breathing can markedly improve the dancer's physiological activation and performance. Moreover, the proposed model can accurately identify the correlation between breathing patterns and dancers' movements, providing scientific support for the application of breathing techniques in dance training in the future.

Keywords: modern dance; breathing techniques; motion recognition; deep learning; biomechanics

1. Introduction

Breathing techniques play an essential role in modern dance, directly affecting the physical expressiveness of dancers and serving as crucial support for their balance and coordination. In modern dance, breathing techniques are about obtaining oxygen and maintaining the physical energy required for movement. Moreover, they are a highly coordinated internal control mechanism of the body that can profoundly influence the fluidity, control, and expressiveness of a dancer's movements [1,2]. In recent years, with the advancement of sports science and biomechanics, the role of breathing techniques in different athletic performances has attracted widespread attention from researchers. However, specific studies on the manifestation of breathing in dance, especially in modern dance, remain relatively limited. Therefore, conducting a biomechanical analysis of how breathing techniques affect dancers' physical control, balance, and coordination is particularly important.

In the relationship between breathing techniques and dance performance, the rhythm, depth, and control methods of breathing are all considered to have a profound impact on dancers' physical stability and expressive movement. Specifically, breathing can help dancers maintain their center of gravity during movements, promoting effective coordination between different muscle groups and thus achieving better physical balance [3]. The rapid transitions and complex movements in modern dance require dancers to maintain body balance in intricate dynamic processes. The correct application of breathing techniques can help dancers display fluidity more freely on stage. Therefore, an in-depth exploration of the biomechanical effects of breathing techniques on balance and coordination can provide dancers with more refined training bases and enhance their technical performance.

With the development of deep learning (DL) technology, algorithms such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have shown excellent performance in image recognition and time series data analysis [4]. The application of DL technology in dance research is gradually emerging, especially in motion recognition and pattern analysis. For instance, Wang et al. [5] studied a multimodal digital twin model based on deep transfer learning, demonstrating the potential advantages of integrating multimodal data in motion recognition analysis. DL models can automatically analyze and recognize dancers' movements under various breathing patterns, identifying changes in balance and coordination, thereby offering more scientific data support for the optimization of breathing techniques. In this study, DL models are used to parse the characteristics and patterns of dancers during the coordination process of breathing and movement, bringing breakthroughs to the scientific analysis of breathing techniques.

Consequently, this study explores the impact of breathing techniques on dancers' balance and coordination through biomechanical analysis. The study employs modern biomechanical measurement techniques to collect dancers' movement data and combine DL models to analyze the characteristics of movement performance under different breathing patterns. To this end, it hopes to reveal how breathing techniques can help dancers better control their bodies. Meanwhile, feasible breathing training guidelines are expected to be proposed by applying DL models in data analysis, providing practical advice for dancers to enhance their expressiveness. The innovation of this study lies in integrating DL and biomechanics, with systematic, automated data processing and precise experimental design. Hence, the study enables the quantification and visualization of the role of breathing techniques in dance performance, promoting the development of dance scientific research in a more precise direction.

2. Recent related work

2.1. Research progress on the effects of breathing techniques on dancers' physiology and performance

The role of breathing techniques in dancer training is widely recognized. Research on the impact of different breathing patterns on dancers' physiological performance has begun to take shape. It reveals that breathing techniques are closely related to changes in heart rate, muscle tension, and nervous system activity, thereby laying a foundation for subsequent studies. For instance, Harbour et al. [6] integrated various evidence-based breathing strategies to enhance human running performance. The study provided athletes and dancers with scientifically grounded breathing techniques to optimize physiological performance. Virtanen et al. [7] explored body awareness in dancers, athletes, and adults engaging in light physical activity, revealing the crucial role of dancers' breathing techniques in their body control and expressiveness. Sun [8] emphasized the importance of breathing training in ethnic dance instruction, arguing that breath control could enhance dancers' movement stability and elevate the artistic impact of their performances. Lopes et al. [9] studied breathing patterns in cycling, suggesting that the lower chest played a more significant role in breath control than the upper chest, offering dancers new insights to optimize breathing efficiency.

In sports activities, breathing techniques have been proven to significantly enhance athletic performance and physiological states. For instance, Jakubovskis et al. [10] found that deep breathing training could help swimmers improve their endurance and reduce lactic acid accumulation, enhancing recovery after exercise. In addition, Sikora et al. [11] demonstrated that respiratory control skills significantly impacted the runners' cardiorespiratory function and exercise efficiency. Especially, during prolonged high-intensity activities, a proper breathing rhythm could effectively delay the onset of fatigue. In other performing arts, breathing techniques also play a crucial role. For example, Wang [12] discovered that breath control in singing training directly affected the singer's tone stability and pitch control ability. Through specific diaphragmatic breathing training, singers could better regulate their breath, enhancing breath support and expressiveness during performance. Furthermore, Ley [13] explored the breathing techniques of actors in theatrical performances. The results indicated that optimizing breathing rhythms could help actors maintain higher physical levels and emotional engagement during long monologues, thereby enhancing the overall fluency and impact of the performance. These studies show that the application of breathing techniques in various performing arts and sports not only improves participants' physiological adaptability but also enhances the precision and stability of performance. They provide valuable insights for further understanding the relationship between respiration and athletic performance. Especially, in the physical art form of dance, the impact of breathing on dancers' physical strength, coordination, and expressiveness is particularly significant.

2.2. Biomechanical mechanisms of breathing techniques on balance and coordination

In the field of modern dance, the application of deep breathing technology has been proven by several studies to significantly improve the expressiveness and physiological state of dancers [14]. For example, Răvdan [15] found that deep breathing in singing and dancing performances not only improved the actor's lung capacity but also played a positive role in conveying emotions during the performance. By adjusting the rhythm of their breathing, dancers can better control muscle strength and physical exertion during their performances, improving the precision and fluidity of their performances. From a biomechanical perspective, the changes in thoracic and abdominal pressure during breathing play a crucial role in supporting core muscle groups, particularly during high-difficulty transitions. Appropriate breathing can help dancers stabilize their bodies and adjust their center of gravity, thus enhancing balance. For example, Kim et al. [16] investigated the effects of different breathing methods on static balance abilities. They found that deep breathing significantly improved balance stability, revealing the biomechanical regulatory role of breathing in balance control. Grissom et al. [17] enhanced patients' balance and coordination through remote healthcare's wake-breath coordination trials, validating the importance of breathing training in clinical recovery and providing new insights into the study of balance biomechanics. Seifert et al. [18] examined the effects of breathing conditions on the coordination of elite Paralympic swimmers. They discovered that the focus on breathing influenced coordination symmetry, underscoring the core role of breathing in balance and movement coordination.

2.3. Current applications of DL in dance motion analysis

DL technology shows great potential in the recognition and analysis of dance movements, particularly through the successful application of CNNs and RNNs in image processing and time series data analysis, which offers new perspectives for dynamic motion recognition in the dance field. For instance, Zhang [19] optimized the matching of technical movements and music for ethnic dance using DL. The results indicated that this method significantly enhanced the fluidity and rhythmic coordination of dance movements, promoting the development of intelligent dance analysis. Parthasarathy and Palanichamy [20] generated a new video benchmark dataset for Indian dance gestures and applied DL for real-time gesture recognition, establishing a solid data foundation for the automatic identification of dance gestures. Jiang and Yan [21] constructed a DL framework using sensor data to generate cohesive dance motion models, revealing the efficient application potential of DL in dance motion generation and consistency analysis.

2.4. Research gaps and the entry point of this study

Despite the gradual recognition of the role of breathing techniques in dance, current research primarily focuses on the physiological support of breathing for basic movement performance, lacking an in-depth exploration of the specific mechanisms underlying balance and coordination. Additionally, existing DL technologies in dance motion analysis mainly address single motion recognition, and the integrated analysis of multi-layered movement performance characteristics remains insufficient. This study combines biomechanical analysis with DL models by experimentally collecting dance data from dancers under different breathing techniques. It investigates the impact of breathing techniques on balance and coordination while leveraging DL technology for systematic data mining. This demonstrates the dual effects of breathing techniques on dancers' physiological states and expressiveness, thus offering new theoretical and technical support for modern dance training.

3. Biomechanical analysis methods for breathing techniques on dancers' expressiveness

3.1. Experimental design and data collection analysis

This study employs an experimental research design to analyze the effects of various breathing techniques on the balance and coordination of modern dancers. The participants consist of 29 modern dancers with a certain level of dance training, aged between 18 and 30 years, all in good health. To ensure sample balance, participants' basic information and dance experience, including years of dancing and styles practiced, are collected through questionnaires before the experiment. The experiment is set up in three groups: the deep, shallow, and general breathing groups. Each group is required to perform the same dance movements for a comparative analysis of their performance under different breathing techniques. Consent is obtained from all participants for this study.

The experimental process is divided into two main stages: the training and the data collection. In the training stage, participants receive guidance on various breathing techniques to ensure they can accurately apply the learned skills during actual dance performances. The training content includes adjusting breathing rhythms and controlling the depth and frequency of breath. In the data collection stage, participants perform standardized dance movements, preceded by appropriate breathing technique exercises to ensure consistency in their breathing during the movements. The experiment utilizes high-frequency motion sensors and high-definition video equipment to record dancers' physiological indicators and motion trajectories while executing specific dance movements. The specific allocation of experimental groups is detailed in **Table 1**.

Table 1. Allocation of experimental groups in a questionnaire survey.

Groups	Breathing techniques	Number of participants	Training content	Data collection method
The deep breathing group	Deep breathing	10	Breathing rhythm and depth control	Motion sensors and camera equipment
The shallow breathing group	Shallow breathing	10	Respiratory rate and rhythm regulation	Motion sensors and camera equipment
The general breathing group	General breathing	9	Maintaining a natural state without interfering with breathing	Motion sensors and camera equipment

Table 1 presents the allocation of experimental groups and related information for this study, aiming to display the participants' training and data collection process under diverse breathing techniques. The experiment consists of three groups: the general, shallow, and deep breathing groups, each utilizing different breathing techniques. The number of participants varies across groups, with 10 participants in both the deep and shallow breathing groups, and 9 participants in the general breathing group. Physiological indicators such as heart rate, respiratory rate, and Surface Electromyography (sEMG) are measured using motion sensors and camera equipment. Additionally, the dancers' performances are recorded via cameras, and subsequent motion recognition and analysis are conducted using image processing techniques. The video data can provide visual evidence of the dancers' performance under different breathing techniques. The training content includes controlling breathing rhythm, depth, and frequency to ensure participants can accurately apply the learned techniques during the experiment.

3.2. Data preprocessing analysis

After data collection is completed, the collected original data should be preprocessed to ensure the accuracy and reliability of subsequent analysis. The data preprocessing process is displayed in **Figure 1**.

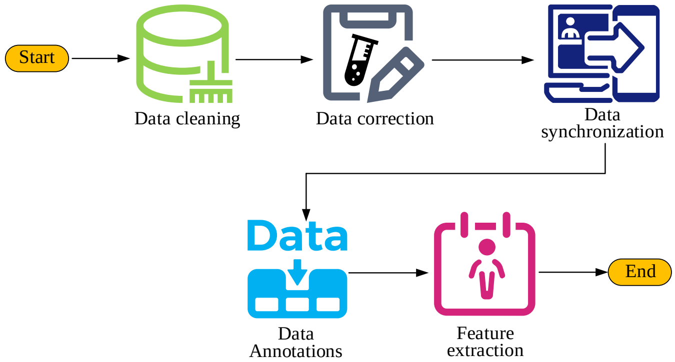

Figure 1. The data preprocessing process.

In **Figure 1**, the first step of preprocessing is data cleaning, which involves removing incomplete or anomalous data points. For instance, in physiological monitoring, data anomalies may occur due to equipment malfunctions or environmental interference, and these must be identified and removed using predefined threshold standards. Furthermore, to ensure that the data obtained from motion sensors and camera equipment can be effectively utilized, algorithms are used to calibrate the data and eliminate noise caused by external environmental factors.

The next critical step in preprocessing is data synchronization. Since different devices may have varying collection frequencies, it is necessary to align all physiological data with the motion trajectory data in terms of time. This process involves matching timestamps from different datasets, ensuring that at any given time, the participant's physiological state corresponds with their motion performance. By employing interpolation methods and temporal resampling techniques, effective integration of data from different sources is achieved, laying the foundation for subsequent analysis.

After data collection, the original data needs to be pre-processed to ensure the accuracy and reliability of subsequent analysis. The process of data preprocessing mainly includes three steps: noise removal, signal synchronization, and feature extraction. Since motion sensors and physiological monitoring devices may be affected by environmental noise or equipment errors during data acquisition, a low-pass filter (LPF) is used to remove noise. The LPF can effectively remove high-frequency noise and retain the main components of the signal. Specifically, an LPF with a cut-off frequency of 10Hz is selected based on Nyquist's theorem, ensuring that the signal frequency is less than half of the sampling frequency. The filter function is shown in Equation (1):

$$H(f) = \frac{1}{1 + (\frac{f}{f_c})^{2n}} \tag{1}$$

$H(f)$ and n represent the frequency response and the order of the filter; f refers to the signal frequency, which is the cut-off frequency. With this method, unwanted high-frequency noise can be removed, and the active components of motor and physiological signals can be preserved.

Because motion sensors and physiological monitoring devices can have different sampling frequencies, the signals collected by different devices need to be time-aligned. To achieve this, a linear interpolation method is employed, which converts all signal data into a uniform timeline. First, it can be assumed that at moment t_i, the data of sensors 1 and 2 are $x_1(t_i)$ and $x_2(t_i)$. For data between time t_i, if the sampling points of sensors 1 and 2 are different, the value of one sensor is mapped to the time point of the other sensor using a linear interpolation equation, as follows:

$$x_1(t) = x_1(t_i) + \frac{(t - t_i)}{(t_{i+1} - t_i)}(x_1(t_{i+1}) - x_1(t_i) \tag{2}$$

t refers to the target time point; t_i and t_{i+1} are adjacent moments of sensor sampling. With this approach, data from different devices can be synchronized to the same timescale, ensuring data consistency at the same point in time. Once the noise removal and signal synchronization are complete, the next step is to perform feature extraction. Time-domain and frequency-domain feature extraction methods are used to extract representative features, such as heart rate, respiratory rate, and muscle activation rate, from the cleaned signal. These features are essential for subsequent motion recognition and physiological analysis.

Finally, data labeling and feature extraction are vital steps to ensure the accuracy of the analysis. The physiological data are categorized according to the participants' states under diverse breathing techniques, enabling clear comparisons of performance between the groups in later analyses. **Figure 1** illustrates the overall flow of data preprocessing, providing a clearer understanding of the various stages of data handling.

3.3. Construction and analysis of dancer's motion recognition model based on DL under various breathing techniques

This study employs a DL model that integrates the Transformer network [22,23] and Three-Dimensional Convolutional Neural Network (3D CNN) [24], aimed at analyzing the impact of different breathing techniques on dancers' performance. This hybrid model processes time-series data and effectively extracts spatial features, offering a more comprehensive understanding of the relationship between breathing and dance movements. Through this innovative network structure, the study can more accurately identify changes in dancers' balance and coordination under different breathing states, providing strong support for data analysis. The architecture of the DL-based motion recognition model for dancers under various breathing techniques is depicted in **Figure 2**.

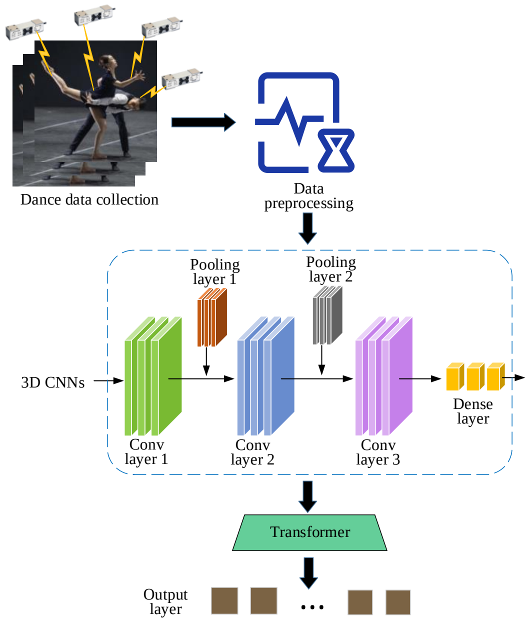

Figure 2. Architecture of the DL-based motion recognition model under different breathing techniques.

In **Figure 2**, the model adopts a multi-layered architecture to effectively analyze dancers' performance with diverse breathing techniques. First, dance data are collected through high-frequency motion sensors and cameras to ensure comprehensive motion trajectories and physiological indicators. The data preprocessing phase includes steps such as cleaning, synchronization, and feature extraction to ensure data quality and consistency. Next, the 3D CNN module, with the help of convolutional and pooling layers, extracts spatial and temporal features from the input video data, capturing subtle changes in the dancer's movements. The Transformer network then enhances long-distance dependencies between features through a self-attention mechanism, enabling the model to more precisely understand the effect of breathing techniques on dance motions. Finally, the output layer classifies the processed features, generating performance probabilities under different breathing techniques to provide data support for subsequent analysis and evaluation. This structure enables the model to integrate diverse information comprehensively and explore the complex relationship between breathing and dance performance in depth.

In this model, features are computed from the spatial and temporal dimensions to capture motion information in multiple consecutive frames. The value of the unit with the position coordinates of (*x*, *y*, *z*) in the *j*th feature diagram of the *i*th layer, as expressed in Equation (3):

$$V_{ij}^{xyz} = f\left(b_{ij} + \sum_{r}\sum_{l=0}^{l_i-1}\sum_{m=0}^{m_i-1}\sum_{n=0}^{n_i-1}\rho_{ijr}^{lmn} v_{(i-1)r}^{(x+l)(y+m)(z+n)}\right) \tag{3}$$

The time dimension of the 3D convolutional kernel is n_i; The weight value of the convolutional kernel where the position (*l*, *m*, *n*) is connected to the *r*th feature map is ρ_{ijr}^{lmn}. V_{ij}^{xyz} represents the value of the unit at position (*x*, *y*, *z*) of the *j*th feature map of the *i*th layer, where *x*, *y*, and *z* are the coordinates of the spatial dimension, respectively. b_{ij} refers to the bias term of the jth feature map of the ith layer, which is used to adjust the output of the feature map. $\sum_r \sum_{l=0}^{l_i-1} \sum_{m=0}^{m_i-1} \sum_{n=0}^{n_i-1} \cdot$ represents a quadruple sum that traverses all relevant feature maps r as well as dimensions l, m, and n in each direction of the convolution kernel. $v_{(i-1)r}^{(x+l)(y+m)(z+n)}$ refers to the value of the unit representing the position ($x + l$, $y + m$, $z + n$) of the rth feature map of the previous layer (the $i-1$ layer). n_i means the temporal dimension of the convolutional kernel in the ith layer, which is the size of the convolution kernel on the time axis. l_j, m_j, and n_j are the spatial dimensions of the jth feature map, representing the size of the convolutional kernel in the x, y, and z directions, respectively. $f(\cdot)$ refers to the ReLU activation function. This function can make the model's parameters sparse, thus reducing overfitting. In addition, it can reduce the amount of computation on the model. The ReLU activation function is defined as Equation (4):

$$f(x) = max(0, x) = \begin{cases} 0, & x \leq 0 \\ x, & x > 0 \end{cases} \tag{4}$$

The calculation of maximum pooling in the model reads (Equation (5)):

$$V_{x,y,z} = \max_{0 \leq i \leq s_1, 0 \leq j \leq s_2, 0 \leq k \leq s_3} \left(\mu_{x \cdot s+i, y \cdot t+j, z \cdot r+k}\right) \tag{5}$$

μ represents the 3D input vector; V denotes the output after the pooling operation; s, t, and r are the sampling steps in the direction. The Softmax function is often used in the last layer of a classification task to map an n-dimensional vector x to a probability distribution. Hence, the correct class probability approaches 1, the other probabilities approach 0, and the sum of the probabilities of all classes is 1.

The extracted features are fed into the Transformer module. Transformer uses a self-attention mechanism to capture long-distance dependencies between features. The calculation of $Attention(Q, K, V)$ can be written as Equation (6) :

$$Att(Q, K, V) = soft\,max\left(\frac{Q \cdot K^T}{\sqrt{d_k}}\right) \cdot V \tag{6}$$

Q, K, and V refer to the matrix of the "query", "key", and "value" vectors.

The change of the multi-head attention mechanism is to perform an N-order linear mapping of the matrices Q, K, and V, which is calculated as Equations (7)–(9):

$$MultiHeadAtt_i = Att(QW_i^Q, KW_i^K, VW_i^V) \tag{7}$$

$$MultiHeadAtt = concat(Att_1, Att_2, \cdots, Att_N) \tag{8}$$

$$Y = MultiHeadAtt_i \cdot W^O \tag{9}$$

W_i^Q, W_i^K, W_i^V is the representation of the ith head, and finally all the heads are spliced together to get the final representation $MultiHeadAtt$. Then the linear transformation with the parameter W^O yields Y. W^O refers to the linear mapping matrix that fuses these N representations. The calculation of Att_i is as follows Equation (10):

$$Att_i = \frac{\left(\frac{Q_i \cdot K_i^T}{\sqrt{d_k}}\right)}{\sum_i \left(\frac{Q_i \cdot K_i^T}{\sqrt{d_k}}\right)} \cdot V_i \tag{10}$$

Q_i, K_i, and V_i represent the mapping matrices of the original input to the *i*-th subspace, respectively.

Finally, the features processed by the Transformer are classified through the output layer, and the performance characteristics of dancers' movements under different breathing techniques are output. The output layer uses a fully connected network, and the probability distribution for each breathing technique is calculated by the softmax function to evaluate the balance and coordination of the dancers. During the training of the whole model, the cross-entropy loss function $\varsigma(y)$ is used to optimize the parameters, as shown in Equation (11):

$$\varsigma(y) = -\sum_{i=1}^{N} y_i \, log(\hat{y}_i) \tag{11}$$

y_i refers to the real label; $\hat{y}_i$ denotes predicted probability; N represents the total number of samples.

This study employs a hybrid model based on DL, combining Transformer networks and 3D CNN, to analyze the effects of different breathing techniques on dancer performance. This model can effectively process time series data and extract spatial features, thus gaining a more comprehensive understanding of the relationship between breathing techniques and dancer movements. The architecture of the motion recognition model based on 3D CNN and Transformer is plotted in **Figure 3**.

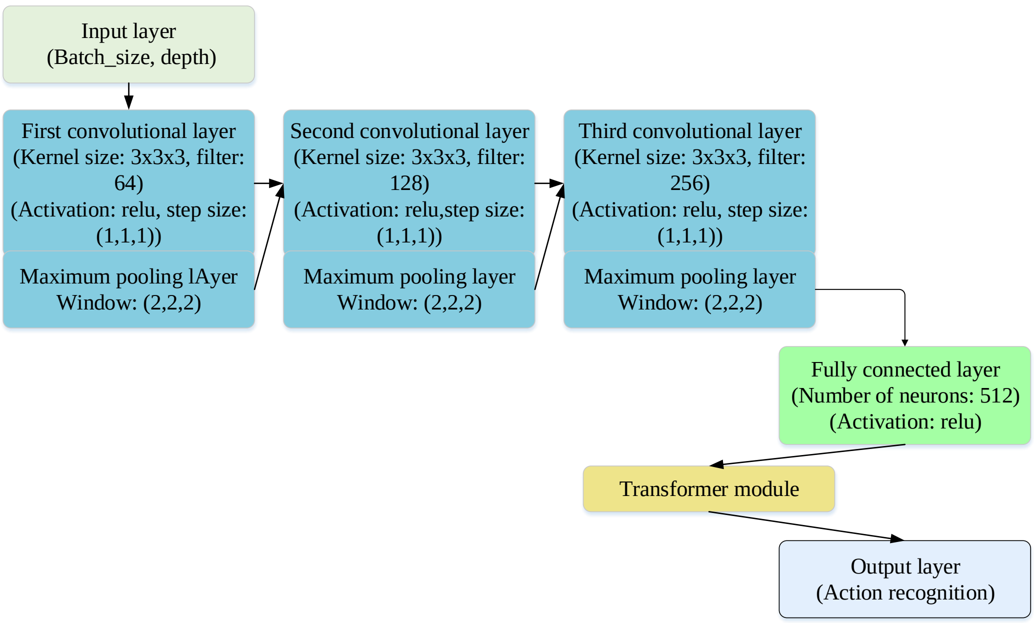

Figure 3. Architecture of the motion recognition model based on 3D CNN and transformer.

The 3D CNN layers in the model consist of multiple convolutional and pooling layers, with specific parameter settings as follows. The shape of the input data is batch_size, depth, height, width, and channels. Where depth refers to the number of temporal frames; height and width are the spatial dimensions of each frame; channels represent the number of channels in the image. The first convolutional layer uses a 3 × 3 × 3 kernel to extract local spatial and temporal features. A stride is set to (1, 1, 1), meaning the kernel moves with a step size of 1 in time and space dimensions. The number of filters is 64, and the activation function uses ReLU. This is followed by a max pooling layer with a pooling window and stride both set to (2, 2, 2), reducing the spatial dimensions of the feature maps while retaining important features. The second convolutional layer has the same parameters as the first, but the number of filters is increased to 128, and the subsequent pooling layer also performs max pooling. The third convolutional layer further increases the number of filters to 256, maintaining the same kernel size and stride. Finally, there is a fully connected layer with 512 neurons, also using ReLU as the activation function. Through this design, the 3D CNN can effectively extract spatial and temporal features from time-series data, thereby aiding in a better understanding of the dancer's movement performance under different breathing techniques. To display the structure of the model, the network architecture diagram shows the processing of input data, the stacking of convolutional and pooling layers, and the final Transformer module. The parameter settings and functions of each layer are detailed in the study. The choice of kernel size takes into account maintaining high computational efficiency while effectively extracting local spatial and temporal features; smaller kernels help capture finer-grained motion details. A stride of 1 preserves a high resolution of feature maps, and pooling layers with a stride of 2 reduces computational complexity while retaining information. As the network deepens, the number of filters gradually increases (from 64 to 256), aiding in the extraction of higher-level, more abstract features. With a rational layer design and parameter selection, this model can accurately recognize the nuances of a dancer's movements under various breathing techniques while ensuring efficient computation, enhancing the accuracy of motion recognition.

```
Start
Input: Dance data under different breathing states
Output: Classification of dancer action recognition results
# Data preprocessing
def preprocess_data(motion_data)
# 3D CNN module
def create_3d_cnn(input_shape):
    model = models.Sequential()
    model.add(layers.Conv3D(filters=32, kernel_size=(3, 3, 3), activation='relu', input_shape=input_shape))
    model.add(layers.MaxPooling3D(pool_size=(2, 2, 2)))
    model.add(layers.Conv3D(filters=64, kernel_size=(3, 3, 3), activation='relu'))
    model.add(layers.MaxPooling3D(pool_size=(2, 2, 2)))
    model.add(layers.Flatten())
    return model
# Transformer module
def create_transformer(features):
    # Attention mechanism
    attention_output = multi_head_attention(features)
    # Add & Layer normalization
    output = layers.LayerNormalization()(attention_output + features)
    return output
def multi_head_attention(features, num_heads=8):
    attention_heads = []
    for _ in range(num_heads):
        Q, K, V = create_qkv(features)
        attention = layers.Attention()([Q, K, V])
        attention_heads.append(attention)
    # Concatenate all heads
    concatenated_heads = layers.Concatenate()(attention_heads)
    return layers.Dense(features.shape[-1])(concatenated_heads)
# Output layer
End
```

Figure 4. Pseudocode flow of motion recognition for dancers based on DL under different breathing techniques.

Through the application of the model algorithm, the multi-dimensional influence of breathing techniques on dancers' performance can be comprehensively analyzed, which provides an important reference for related theories and practices. The pseudocode flow of this model is presented in **Figure 4**.

3.4. Analysis of measurement methods of physiological and performance indicators

This study also explores the measurement methods for physiological and performance indicators, which are crucial for evaluating dancers' states under different breathing techniques. By combining physiological data (such as heart rate, respiratory rate, and sEMG) with performance indicators (such as balance, coordination, and movement fluidity), the study can comprehensively analyze the effects of breathing techniques on dancers' physiology and performance. This holistic approach offers scientific evidence for understanding the relationship between dancers' physiological responses and movement performance during a performance and provides effective support for optimizing dancers' training and performances. The measurement methods for physiological and performance indicators are suggested in **Figure 5**.

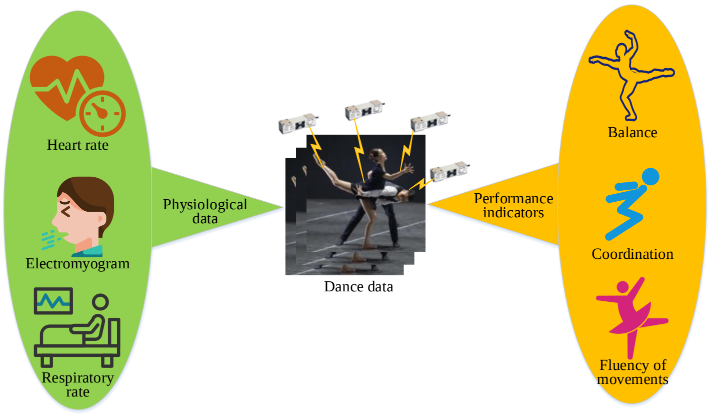

Figure 5. Schematic diagram of measurement methods for physiological and performance indicators.

In **Figure 5**, the measurement methods for physiological indicators primarily include respiratory rate, sEMG, and heart rate. These indicators reflect the dancers' physiological states under different breathing techniques. Heart rate is monitored using a heart rate monitor to record real-time changes in the dancer's heart rate during training and performance, helping analyze the relationship with breathing techniques. The respiratory rate is captured through a breathing monitor, assessing the dancer's breathing pattern with various breathing techniques. In addition, sEMG devices monitor the electrical activity of muscles, offering important data for analyzing muscle activation during specific movements.

Performance indicators focus on the quality and expressiveness of the dancer's movements. These indicators encompass coordination, balance, and movement fluidity. Motion data collected by sensors can calculate the dancer's center of gravity changes and joint angles during performance, which help evaluate balance. Coordination is measured by analyzing the consistency of joint movements when performing complex motions. Furthermore, video analysis software is utilized to analyze the dancer's performance frame by frame, quantifying movement fluidity and evaluating performance variations under different breathing techniques.

3.5. Experimental evaluation

To evaluate the performance of the proposed model, the data used includes dancer information obtained through a questionnaire survey and the Cave Dance Dataset (http://cavedance.art/cave-dance-dataset.html), as illustrated in **Figure 6**. The questionnaire is designed to collect personal information, training habits, and the breathing techniques used by the dancers, to capture their subjective experiences and feedback based on different conditions. Additionally, by combining the open dance motion database, the study integrates a large number of dance videos and physiological data to enrich the sample size and enhance the representativeness of the analysis. The combination of these data sources provides a comprehensive perspective, making the analysis results more reliable.

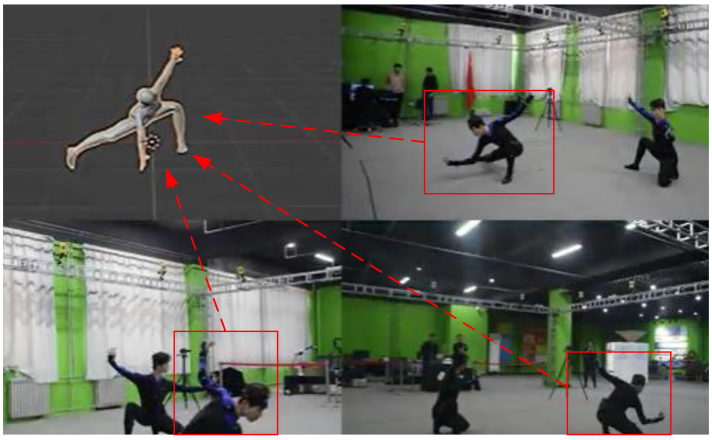

Figure 6. Dance movement collection in the cave dance dataset.

The experimental setup ensures the effectiveness of data collection and model training. The experiments take place in a controlled dance studio, equipped with high-frequency motion sensors, cameras, and physiological monitoring devices to record dancers' movements and physiological states in real-time. Regarding hyperparameter settings, the model uses an initial learning rate of 0.001, a batch size of 32, and 50 training epochs. To prevent overfitting, dropout techniques are applied, with dropout rates set at 0.2, 0.4, 0.5, 0.6, and 0.8, and the training process is adjusted accordingly. Dropout is a commonly used regularization technique in DL, designed to prevent overfitting in neural network models. Different dropout rates can have varying impacts on the training process and the ultimate performance of the model. According to the dropout algorithm proposed by Jiang et al. [25], dropout rates between 0.2 and 0.5 are typically common choices. A dropout rate that is too low may not effectively prevent overfitting, while a rate that is too high could lead to the network being unable to learn features effectively. Based on the research by Omar and Abd El-Hafeez [26], the choice of dropout rate is closely related to the scale and complexity of the network. In smaller networks, a lower dropout rate (such as 0.2) is often used, while in large deep networks, a higher dropout rate (such as 0.5 or higher) helps to improve the model's generalization ability. This study selects a range from 0.2 to 0.8 to comprehensively test the model's performance under different dropout rates and to observe its impact on model accuracy and generalization ability. In the preliminary stage of the experiment, different dropout rates are set and tuned on the validation set, leading to the selection of a dropout rate range from 0.2 to 0.8. The experimental results reveal that at a lower dropout rate (such as 0.2), the model is more prone to overfitting, exhibiting a high training set accuracy but a relatively low validation set accuracy. At higher dropout rates (such as 0.5–0.8), although the model's training accuracy decreases, the validation set accuracy significantly improves, enhancing the model's generalization ability. Based on these preliminary experimental results, it is decided to adopt a dropout rate range from 0.2 to 0.8 in the final experiment to observe its impact on model performance and to select the optimal dropout rate. Moreover, data augmentation techniques are employed to expand the training samples, enhancing the model's generalization ability.

In terms of performance evaluation indicators, the proposed model algorithm is compared with the 3D CNNs [27], 3D ResNets [28], and the study by Jiang and Yan [21], using multiple assessment standards to measure model performance. Key indicators include accuracy and F1 score, comprehensively reflecting the model's recognition performance under various breathing techniques. Furthermore, the biomechanical results of dancers under different breathing patterns are analyzed across the three groups from the questionnaire survey, encompassing heart rate, respiratory rate, and muscle activation rate. This study employs an experimental research design to analyze the impact of different breathing techniques on the physiological state and performance of modern dance performers. Potential confounding variables are controlled to ensure the reliability and validity of the experimental results. Firstly, to exclude the influence of time factors on the experimental outcomes, all experiments are conducted within the same time frame (for example, all between 2 PM and 4 PM). The selection of this time frame is based on physiological research findings. That is, a person's physiological state can vary significantly at different times of the day. Thus, standardizing the experimental timing helps to minimize the interference of this factor. Secondly, before the experiment, all participants are required to provide records of their physical activities from the previous day to ensure they have not engaged in intense exercise or physical activity. Participants are also instructed to maintain at least 12 h of rest to ensure their bodies are in a similar state of recovery. Furthermore, considering individual differences in breathing patterns, such as respiratory rate and tidal volume, baseline measurements are taken before the experiment to assess each participant's basic physiological state and breathing patterns. Based on the individual differences of each participant, personalized adjustments are made to the training content, such as fine-tuning the duration and rhythm of deep and shallow breathing exercises. This ensures that each participant can undergo training and testing in an optimal physiological state. Through these control measures, efforts are made to eliminate the impact of potential confounding variables on the experimental results. Thus, the internal validity of the experiment can be enhanced and the reliability of the research findings can be improved. To further assess the model's stability, K-fold cross-validation is employed to validate its performance across multiple subsets, ensuring its adaptability to new data. These evaluation methods provide quantitative evidence to support the analysis of the impact of breathing techniques on dancers' performance.

4. Results and discussion

4.1. Analysis of motion recognition results of dancers with different algorithms

First, each algorithm's accuracy and F1 score results at different Dropout rates are compared, as suggested in **Figures 7** and **8**.

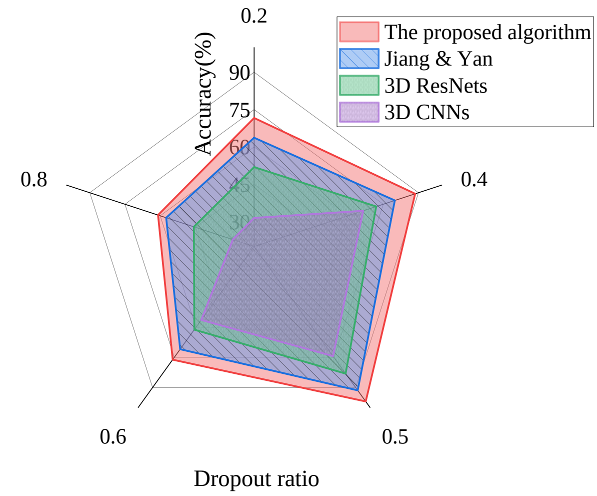

Figure 7. The accuracy of dancers' motion recognition under different algorithms.

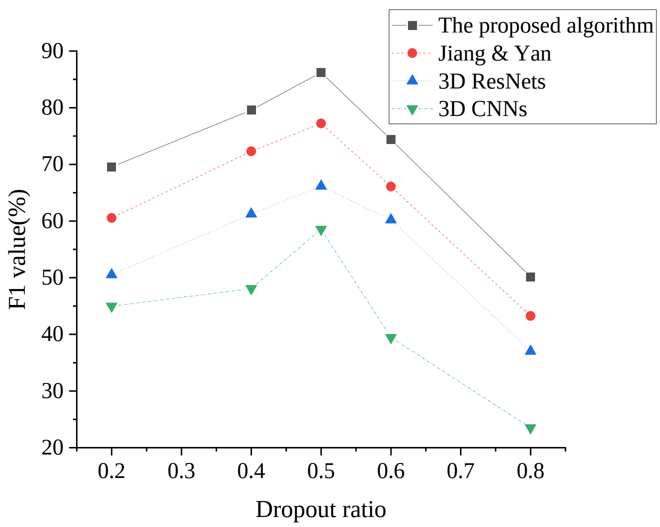

Figure 8. The F1 score of dancers' motion recognition with diverse algorithms.

Figures 7 and **8** indicate that the proposed model algorithm outperforms existing comparison models in terms of accuracy and F1 score at various dropout rates. Specifically, with dropout rates of 0.2 and 0.4, the accuracy and F1 scores of the proposed algorithm reach 71.63% and 88.58%, respectively, significantly surpassing those of other algorithms such as Jiang and Yan [21], 3D ResNets, and 3D CNNs.

Notably, when the dropout rate is set to 0.5, the proposed algorithm's performance is especially remarkable, achieving an accuracy of 96.89% and an F1 score of 86.23%. It demonstrates the model's advantage in preventing overfitting and capturing subtle motion features. Additionally, at higher dropout rates (e.g., 0.8), although the performance of all models decreases, the proposed algorithm exhibits a relatively smaller drop in performance, still outperforming the other algorithms. This suggests that the model shows good stability in handling data uncertainty and enhancing generalization ability. Overall, the proposed algorithm demonstrates excellent advantages regarding accuracy, stability, and anti-overfitting capability.

4.2. Analysis of biomechanical performance results of dancers under diverse breathing techniques

The biomechanical performance results of dancers under three different breathing techniques in the deep, shallow, and general breathing groups are further analyzed, as revealed in **Figure 9**.

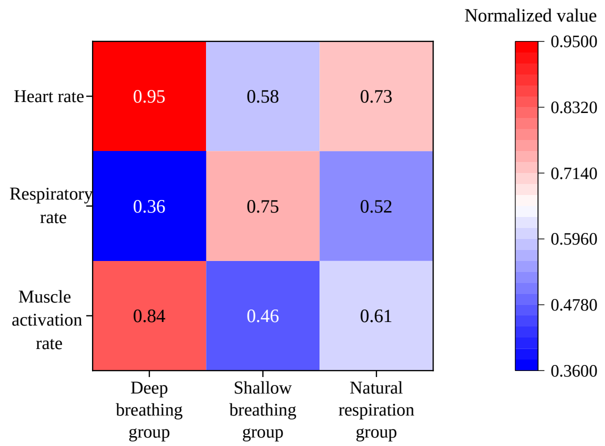

Figure 9. Biomechanical results under various breathing techniques.

In **Figure 9**, the biomechanical performance of dancers varies under different breathing techniques. Deep breathing shows significant advantages in heart rate, respiratory rate, and muscle activation rate. Specifically, the heart rate for the deep breathing group is 0.84, much higher than the shallow and general breathing groups at 0.46 and 0.61. It illustrates that deep breathing is more effective in enhancing the dancer's physiological activation level. Additionally, the respiratory rate for the deep breathing group is only 0.36, lower than the general and shallow breathing groups. It suggests that deep breathing can more effectively control the breathing rhythm and help the dancer maintain a stable state. Regarding muscle activation rate, the deep breathing group shows a clear advantage, reaching 0.95, significantly higher than the shallow breathing group's 0.58 and the general breathing group's 0.73. This result indicates that deep breathing can better engage the body's muscles, helping to improve the dancer's expressiveness and control. Overall, deep breathing positively impacts the dancer's physiological state and expressiveness.

To comprehensively assess the model's performance, a 5-fold cross-validation was employed, and the average accuracy, standard deviation (SD), and confidence interval (CI) (95%) under different dropout rates are calculated. The cross-validation results are outlined in **Table 2**. It shows significant variations in the model's average accuracy, SD, and CI under different dropout rates. Specifically, when the dropout rate is 0.5, the model demonstrates the best average accuracy (96.89%), with the smallest SD (±1.36%) and the narrowest CI ([95.18%, 98.60%]). It indicates that the model's performance is the most stable and reliable under this configuration. In contrast, when the dropout rate is 0.2, the model has a lower accuracy (92.34%) and a larger SD, showing higher performance variability. As the dropout rate increases, the accuracy generally improves until 0.5. The dropout rate is further increased to 0.6 and 0.8, resulting in a slight decrease in accuracy and increased variability, reflected in larger SD and CI.

Table 2. Results of cross-validation.

Dropout rate	**Average accuracy (%)**	**SD (%)**	**CI (95%)**
0.2	92.34	±2.05	[90.34%, 94.34%]
0.4	94.61	±1.89	[92.54%, 96.68%]
0.5	96.89	±1.36	[95.18%, 98.60%]
0.6	94.23	±2.02	[92.12%, 96.34%]
0.8	90.87	±2.34	[88.12%, 93.62%]

To further verify the significant impact of different dropout rates on model performance, a one-way analysis of variance (ANOVA) is conducted, as detailed in **Table 3**. The results indicate that the dropout rate remarkably affects the model's accuracy (F = 18.67, p < 0.05), suggesting that adjustments to the dropout rate significantly influence model performance. Specifically, a dropout rate of 0.5 is determined to be the optimal configuration in this study, as it ensures high accuracy while minimizing performance variability.

Table 3. Results of one-way ANOVA.

Dropout	***F*-value**	***p*-value**
0.2	12.45	0.002
0.4	14.32	0.001
0.5	18.67	<0.05
0.6	11.89	0.005
0.8	9.76	0.01

5. Conclusion

This study has reached several important conclusions by analyzing the impact of different breathing techniques on modern dance performers' physiological state and expressiveness. Particularly, it highlights the positive effects of deep breathing techniques on the performers' expressions. The experimental results show that deep breathing not only markedly improves the dancers' heart rate and muscle activation but also effectively regulates breathing rhythm, thereby enhancing the dancers' expressiveness and body control. Based on these findings, it is recommended that deep breathing techniques be applied at all stages of dance training, especially during warm-up and relaxation. By engaging in 3–5 min of deep breathing exercises before and after training, dancers can improve oxygen supply, relax muscles, and reduce the risk of injury. Additionally, practicing deep breathing in conjunction with different dance movements can help dancers maintain a sense of rhythm and fluidity in complex movements, thus enhancing coordination and control. The study also indicates that deep breathing markedly increases muscle activation and heart rate, thus improving dance expressiveness. Dancers should consciously adjust their breathing rhythm and depth during training to ensure that deep breathing enhances the power and expressiveness of their movements. The effects of deep breathing vary across different types of dance. It is critical for modern dance, which requires high body control and muscle activity. Moreover, for ballet and other styles that demand softness and fluidity, deep breathing helps improve posture control and stability. When implementing deep breathing techniques, dancers should adjust their breathing rhythm and depth to avoid over-inhaling or exhaling, maintaining a natural and comfortable breathing state to avoid discomfort. Furthermore, beginners should adopt a progressive training approach, starting with basic deep breathing exercises and gradually increasing the duration and intensity to prevent physical discomfort.

However, the study has some limitations, such as a small sample size and a single data source. Future work could expand the sample size and include analysis of breathing techniques across different dance styles and environments. Looking ahead, further optimization of the model structure, incorporation of multimodal data, and broader application scenarios contribute to advancing the in-depth research on breathing techniques in enhancing dance expressiveness.

Ethical approval: Not applicable.

Conflict of interest: The author declares no conflict of interest.

References

1. Jianu A, Iorga A. The Influence of Psychokinetic Therapy on Stress and Motor Performance in Young Dancers Aged 18-19 Years. Psychology, 2024, 15(5): 825-848.
2. Gusmail S, Nugra P D, Syahrizal S. The impact of diaphragmatic breathing on the endurance of contemporary dancers at the Institut Seni Budaya Indonesia Aceh: model-based experimental design. Gelar: Jurnal Seni Budaya, 2023, 21(2): 115-127.
3. Ko K S, Lee W K. A preliminary study using a mobile app as a dance/movement therapy intervention to reduce anxiety and enhance the mindfulness of adolescents in South Korea. The Arts in Psychotherapy, 2023, 85: 102062.
4. Aljohani A. Predictive analytics and machine learning for real-time supply chain risk mitigation and agility. Sustainability, 2023, 15(20): 15088.
5. Wang J, Qiao L, Lv H, Lv Z. Deep transfer learning-based multi-modal digital twins for enhancement and diagnostic analysis of brain MRI image. IEEE/ACM Transactions on Computational Biology and Bioinformatics, 2022, 20(4): 2407-2419.
6. Harbour E, Stöggl T, Schwameder H, Finkenzeller T. Breath tools: a synthesis of evidence-based breathing strategies to enhance human running. Frontiers in Physiology, 2022, 13: 813243.
7. Virtanen N, Tiippana K, Tervaniemi M, et al. Exploring body consciousness of dancers, athletes, and lightly physically active adults. Scientific Reports, 2022, 12(1): 8353.
8. Sun X. The Importance of Breathing Training in Folk Dance Teaching. Journal of Contemporary Educational Research, 2024, 8(4): 187-192.
9. Lopes AL, Sarro KJ, Rodrigues IM, et al. Breathing Motion Pattern in Cyclists: Role of Inferior against Superior Thorax

Compartment. International Journal of Sports Medicine, 2024, 45(06): 450-457.
10. Jakubovskis G, Zuša A, Solovjova J, et al. Effects of breathing exercises on young swimmers' respiratory system parameters and performance. Molecular & Cellular Biomechanics, 2024, 21(1): 205-205.
11. Sikora M, Mikołajczyk R, Łakomy O, et al. Influence of the breathing pattern on the pulmonary function of endurance-trained athletes. Scientific Reports, 2024, 14(1): 1113.
12. Wang Y. The effectiveness of innovative technologies to manage vocal training: The knowledge of breathing physiology and conscious control in singing. Education and Information Technologies, 2024, 29(6): 7303-7319.
13. Ley D. Innovating Cross-Disciplinary Methods for Performance Voice: My Journey Applying Massage Therapy to Actor Training. Voice and Speech Review, 2023, 17(3): 369-379.
14. Gang Y, Zhang B. A Study on the Impact of Dance Flow on Individual Creative Expression. Art and Society, 2023, 2(5): 34-38.
15. Răvdan G V. Collaborative tools in the development of opera singers' bodily. Învăţământ, Cercetare, Creaţie, 2023, 9(1): 357-368.
16. Kim SH, Shin HJ, Cho HY. Impact of Types of Breathing on Static Balance Ability in Healthy Adults. International Journal of Environmental Research and Public Health, 2022, 19(3): 1205.
17. Grissom CK, Holubkov R, Carpenter L, et al. Implementation of coordinated spontaneous awakening and breathing trials using telehealth-enabled, real-time audit and feedback for clinician adherence (TEACH): a type II hybrid effectiveness-implementation cluster-randomized trial. Implementation Science, 2023, 18(1): 45.
18. Seifert L, Létocart A, Guignard B, Regaieg MA. Effect of breathing conditions on relationships between impairment, breathing laterality and coordination symmetry in elite para swimmers. Scientific Reports, 2024, 14(1): 6456.
19. Zhang A. Optimization Simulation of Match between Technical Actions and Music of National Dance Based on Deep Learning. Mobile Information Systems, 2023, 2023(1): 1784848.
20. Parthasarathy N, Palanichamy Y. Novel video benchmark dataset generation and real-time recognition of symbolic hand gestures in Indian dance applying deep learning techniques. ACM Journal on Computing and Cultural Heritage, 2023, 16(3): 1-19.
21. Jiang H, Yan Y. Sensor based dance coherent action generation model using deep learning framework. Scalable Computing: Practice and Experience, 2024, 25(2): 1073-1090.
22. Li B, Cui W, Zhang L, et al. Difformer: Multi-resolutional differencing transformer with dynamic ranging for time series analysis. IEEE Transactions on Pattern Analysis and Machine Intelligence, 2023, 45(11): 13586-13598.
23. Zhou Q, Li M, Zeng Q, et al. Let's all dance: Enhancing amateur dance motions. Computational Visual Media, 2023, 9(3): 531-550.
24. Li Z. Image analysis and teaching strategy optimization of folk dance training based on the deep neural network. Scientific Reports, 2024, 14(1): 10909.
25. Jiang P, Xue Y, Neri F. Continuously evolving dropout with multi-objective evolutionary optimisation. Engineering Applications of Artificial Intelligence, 2023, 124: 106504.
26. Omar A, Abd El-Hafeez T. Optimizing epileptic seizure recognition performance with feature scaling and dropout layers. Neural Computing and Applications, 2024, 36(6): 2835-2852.
27. Chen G. An interpretable composite CNN and GRU for fine-grained martial arts motion modeling using big data analytics and machine learning. Soft Computing, 2024, 28(3): 2223-2243.
28. Li J, Gong R, Wang G. Enhancing fitness action recognition with ResNet-TransFit: Integrating IoT and deep learning techniques for real-time monitoring. Alexandria Engineering Journal, 2024, 109: 89-101.