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# Innovation of Teaching Mode and Enhancement of Artistic Performance in Film and Television Acting Supported by Artificial Intelligence

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**SUMMARY:** *Teaching mode, as the core element of artistic expression, directly affects the aesthetic expression and emotional transmission of students' works. Based on the application of style migration algorithm supported by artificial intelligence in teaching, this paper analyzes its effect on the innovation of teaching mode and the enhancement of artistic expression. The research adopts a mixed method of technology development and effect evaluation, selects a variety of film and television works with distinctive performance characteristics, and uses convolutional neural networks to extract their performance feature vectors and construct a style database. A style migration system based on generative adversarial network is developed to stylize the new performance materials. The effect of the algorithm is evaluated in three dimensions: content consistency, emotional expression accuracy, and style recognition through expert evaluation and audience perception experiments. It was found that the expert score of the style migration algorithm's target performance style characteristics was (9.1±1.4) points, and the audience perception of the integration of personal style and target style reached (8.8±0.9) points. It is said that the technology not only enhances the teaching efficiency, but also provides new possibilities for students' artistic expression ability. The study shows that algorithmic film and television acting teaching is a powerful tool to strengthen the teaching mode, provide theoretical support and practical reference for enhancing artistic performance, and effectively promote the deep integration of film and television acting teaching and artificial intelligence technology.*

***KEYWORDS:*** *film and television acting; style migration algorithm; teaching model innovation; convolutional neural network; generative adversarial network*

## 1 Introduction

At present, the teaching reform of film and television acting classes in colleges and universities are relatively single, how to adapt to the needs of today's technological development, reforming the teaching of the acting class, so that the acting talent can adapt to the needs of today's social development [1]. Most of the film and television acting students have opened the film and television directing, broadcast hosting, news editing, improvisational commentary and other courses, but the subject setup is relatively biased and unfocused, so that it is easy to focus on learning other courses, these practical skills such as film and television directing, news editing, etc. belong to the category of vocational skills, it is easy to let the students lose sight of the other side of the coin, and did not let the students in the professional performance of the skills to improve the artistic performance is the core competitiveness of acting students [2, 3]. With

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the popularization of computers and the rapid development of digital image and video processing and artificial intelligence technology, how to use computers to assist ordinary people or even replace professional artists for independent artistic creation has been the focus of the industry, and has gradually developed into a multidisciplinary interdisciplinary interdisciplinary research field of digital image and video processing, artificial intelligence, machine vision, computer art, computer graphics, visual cognition and other key research Problems. As the most effective computer-assisted art creation method, style migration has been widely used, and the artistic expression ability can be improved in many ways through style migration techniques [4, 5].

Literature [6] suggests that the rapid development of Artificial Intelligence (AI) has revolutionized the way animation is created, and using case studies such as Spider-Man: Across the Spider-Verse, the study establishes a qualitative analytical framework called “Multi-dimensional Innovation and Integration of Artificial Intelligence in Animation Creation”. Five key feature dimensions were identified: efficiency, intelligence, personalization, cultural integration and diversity. The experimental results found that AI can significantly improve efficiency through automated animation generation and real-time optimization, while intelligent tools can precisely control motion dynamics and emotional expression. Literature [7] suggests that despite the widespread success of Artificial Intelligence (AI) in various fields, its full potential remains largely untapped in the field of education, especially in filmmaking education. Utilizing methods such as a literature course review to address the existing shortcomings, the analysis of the results suggests that the use of AI-generated programs to enhance the effectiveness of filmmaking education has shown significant results. This study not only provides a fresh perspective on the practical application of AI in the field of film education, but also sheds light on innovations in the field of education. Literature [8] proposes that the workload of manual listening for sound classification in film and television performance teaching is huge and cumbersome, constructs two algorithmic models of HMM and BPNN for experiments, and finds that the accuracy of the BPNM model in training is higher than 90%, and introduces new samples to stimulate the training of the expressive ability and stability of the results are good. In addition only the recognition rate of complex sound types of individual sound sources decreased, the HMM model is far from the level obtained by the BPNN training method, so the BPNN model can effectively enhance the art of teaching film and television performances.

Literature [9] for how to choose the best artificial intelligence algorithm, can not accurately judge the nonlinear relationship between the innovative strategy and the film and television post-production program, put forward a dynamic factor integration based on the artificial intelligence algorithm to improve the program for experimentation. The results found that the algorithm in different film and television production requirements, the artificial intelligence algorithm of the innovative strategy selection judgment accurately, better than the traditional film and television production methods, for film and television post-production optimization to provide efficient technical support. Literature [10] proposes that the traditional art field will gradually be replaced by intelligent machines, and utilizes the research ideas that draw on the integration of digital media art and AI to propose a design algorithm based on convolutional neural networks. The feature extraction and classification of art images solves the problem of insufficient research on the classification of existing multi-category art images, and provides technical support for the enhancement of film and television performing arts. Literature [11] proposes that AI technology can drive the innovation of the teaching mode of new media art majors in private colleges and universities, which provides powerful technical support and innovation power for art teaching. By optimizing the curriculum, introducing an optimized curriculum system, introducing intelligent teaching tools, strengthening practical teaching as well as improving teachers' AI literacy, improving teaching quality and fostering practical teaching. It also points out that it should continue to deepen the in-depth integration of AI technology and new media art education, which not only provides a theoretical basis and practical path for the reform of art professional education and teaching, but also provides a useful reference for the in-depth application of AI technology in the field of art education.

Based on AI technology and film and television performance teaching, this paper utilizes the mechanism of the style migration algorithm in influencing the teaching mode, which plays a key role in improving the quality of art performance and performance teaching. A variety of film and television works with performance characteristics are selected, and the generator model and discriminator model are trained to discriminate whether the film and television works are consistent with the actual performance style. With the help of convolutional neural network to extract the performance feature vector, establish a database with perfect performance style, and develop the migration system based on generative adversarial network. The weight coefficients of the loss function are calculated to measure the high-level emotional perception and semantic differences between performances, conditionalize the performance styles, and correct the Gram matrix, so as to complete the stylization of the new performance material. The performance of the algorithm is verified in terms of data preprocessing and the number of generated samples, and the effect of the algorithm is evaluated in terms of three dimensions: color consistency, emotional expression accuracy, and style recognition. It provides technical support and practical path for the innovation of teaching mode of film and television performance, promotes the deep integration of image performance research and artificial intelligence technology, and helps cultivate high-quality performance talents adapted to the development needs of the industry.

# 2 Teaching Mode of Film and Television Acting

## 2.1 Film and television collection

Based on the generative adversarial network selecting a variety of film and television productions featuring performances, the framework trains the generator model $G$ and the discriminator model $D$ at the same time, and the objective of $G$ is to maximize the probability of $D$ making an error [12, 13]. the GAN can be trained by backpropagation and does not require any Markov chain. The value function $V\left(D,G\right)$ for $D$ and $G$ is given in the following equation:

$$\min_G \max_D V(D,G) = E_{X-Pdaia(x)}\left[\log D(x)\right] + E_{z-p_z(z)}\left[\log(1-D(G(z)))\right] \tag{1}$$

where: $x$ denotes real popular movie and television productions, $z$ denotes the noise of the input $G$ network, $G(z)$ is the collection of movies and television generated by the $G$ network, $D(x)$ is the $D$ network to determine whether the movie and television productions have a specific performance style, and $P_{daia}$ is the real movie and television performance style [14].

From the point of view of generator $G$, it is desirable to minimize $\min_G \max_D v(D,G)$. From the point of view of discriminator $D$, it is desirable to maximize $\min_G \max_D v(D,G)$. At the beginning of training, when $G$ is poor, $D$ rejects samples, resulting in $\log(1-D(G(z)))$ saturation. Training $G$ maximizes $\log(1-D(G(z)))$, rather than minimizing

$\log(1-D(G(z)))$ and finally $G$ and $D$ are in relative dynamic equilibrium.

Figure $D$ shows the basic form of a generative adversarial network, 1 discriminant distribution, green dashed line, $P_x$ data generating distribution, black dashed line, $P_x(G)$ generating distribution, yellow solid line, $z$ region sampled, $x$ part of the definitional domain, and $x = G(z)$ upward arrows indicating how the mapping imposes a non-uniform distribution $P_x$ on the transformed samples. $G$ Shrinking in $P_x$ the high-density region, and expanding in the low-density region of $P_g$ the network.

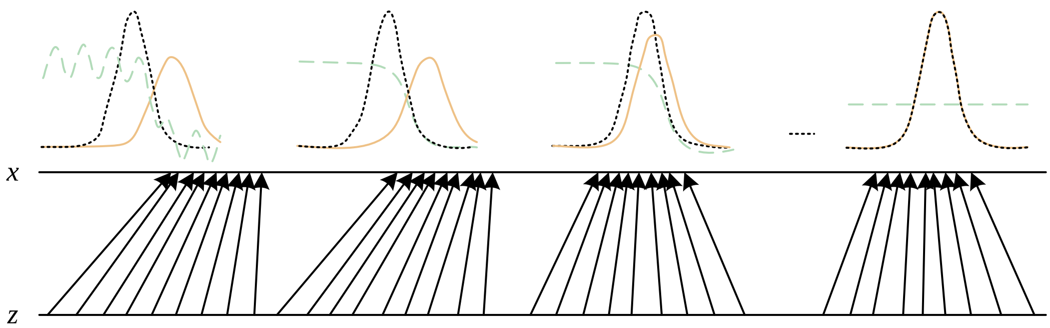



*Figure 1: Basic form of generative adversarial network*

$P_x$ and $P_{data}$ against convergence, and $D$ is a partially accurate classifier. In the algorithm, $D$ is trained from the data to distinguish between the film and television collections, converging to $D^*(x) = \frac{P_{data}}{P_{data(x)+p_g(x)}}$. $G$ is updated, and the gradient of $D$ directs the flow of $G(z)$ to the region that is categorized as the data, and after a few steps of training, G and $D$ will reach an equilibrium point, at which point $P_g = P_{data}$. the discriminator is unable to differentiate between the two distributions, which is $D_x = \frac{1}{2}$, suggesting that film and television productions are essentially the same as the actual performance styles [15, 16].

## 2.2 Database construction

The convolutional layer is the feature extraction part of the Performance Characteristic Style Network, and its purpose is to extract performance style features. When constructing the convolutional layer, the size and step size of the convolutional kernel need to be pre-set. By adjusting the sliding step of the convolution kernel, the feature representation of the desired size can be obtained. The process of convolution can be illustrated with a simple example, Figure 2 shows the convolution layer structure. The example takes a 5×5 style vector as the input data, the size of the convolution kernel is 3×3, the number is 1, and the step size of the convolution operation is 1. The styles of the convolution kernel at each position are multiplied by the corresponding styles of the input, and then summed up, and finally the output feature vectors of the convolution operation can be obtained by calculating the process at all positions of the input data, which can be used to construct the systematic database of the performance styles [17, 18].

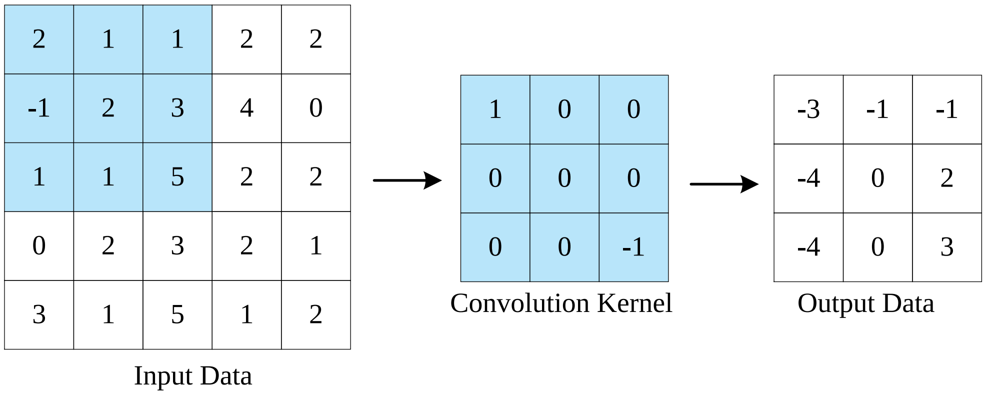



*Figure 2: Structure of convolutional layer*

The structure of the pooling layer is shown in Figure 3, pooling is generally performed after convolution, and the essence of pooling is sampling. It is mainly a dimensionality reduction operation on the performance style feature matrix, so that the feature vector can extract more important features while shrinking, and pooling includes maximum pooling and average pooling [19, 20].

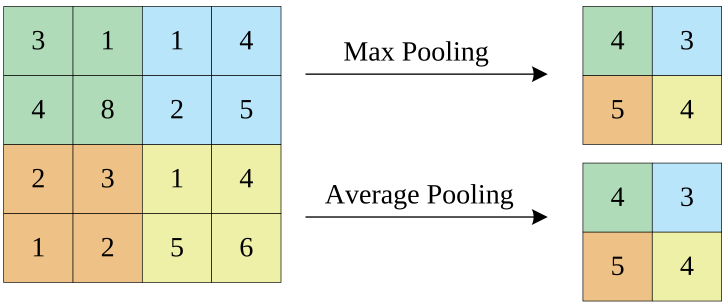



*Figure 3: Pooling layer structure*

The structure of the fully connected layer is shown in Fig. 4, and its main function is to change the multidimensional feature style output from the previous layer into a one-dimensional feature style, which integrates all the performance feature values and facilitates the categorization and teaching task.

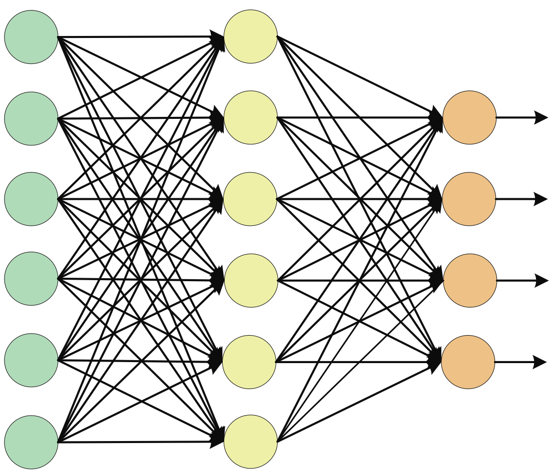


*Figure 4: Fully connected layer structure*

Activation functions mainly include Sigmoid activation function, Tanh activation function, ReLU activation function and Leaky ReLU activation function. The activation function is an important part of the convolutional neural network, which is used to nonlinearly map the feature map output from the convolutional layer and enhance the feature learning ability of the network.The Sigmoid function outputs values between 0 and 1, which is easy to derive but prone to the problem of gradient vanishing, as in the following equation:

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

The Tanh function is a deformation of the Sigmoid function and the output is centered at zero as in the following equation:

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

The ReLU function avoids problems such as gradient vanishing and gradient explosion, which improves the stability of model training and speeds up the convergence of the algorithm as follows:

$$\mathrm{Re}LU(x) = \max(0, x) \tag{4}$$

The LeakyReLU function is similar to the ReLU function, but with a tiny gradient in the part of the input less than 0, which solves the problem that the neurons in the ReLU function can't update the parameters to learn, as in the following equation:

$$Leaky\,\mathrm{Re}LU(x) = \max(ax, x) \tag{5}$$

## 2.3 Evaluation of artistic performance

### 2.3.1 Basis for evaluation

The art style migration algorithm is mainly based on the quality of the generated film and television collection as an evaluation basis, and the evaluation criteria of the artistic performance are divided into two parts: qualitative perception effect and quantitative evaluation index. Qualitative perception standards for the generation of performance characteristics of the degree of restoration and consistency between styles, in the real art style migration field of generation quality evaluation indexes in the structural similarity is used to measure the content and generation of structural similarity, the larger the value is the higher the similarity, the larger the value is the smaller the distortion. Content loss compares the difference between 2 feature maps by feeding the content and generation results into the Cono4 1 layer of the VGG19 model, and the larger the value, the larger the feature map difference. Style loss, on the other hand, is achieved by feeding the style and generation features into the VGG19 model, extracting the features from each of the first 4 layers, calculating the Gram matrix of the 2 feature maps with different scales of features, and expressing the style differences between performances by comparing the co-occurrence correlation between the feature maps, and structural similarity and content loss are reflected by calculating the structural similarity of the content with the generation result and content loss, reflecting the effect of generating the performance content partially The structural similarity and content loss reflect the effect of partial migration of the style of the generated performances by calculating the style loss between the style and the form of the generated performances [21]. The formulas for calculating content loss and style loss are as follows:

$$L_{content} = \|F[O] - F[C]\|_2^2 \quad (6)$$

$$L_{style} = \frac{1}{4N_l^2 M_l^2} \sum_{l=0}^{4} \omega_l \sum_{i,j} (G_{ij}^l - A_{ij}^l)^2 \quad (7)$$

where $L_{content}$ is the content loss, $L_{style}$ is the style loss, $O$ denotes the generated performance form, $C$ denotes the performance content, and $N$ and $M$ represent the performance form and connotation, respectively. $G_{ij}$ and $A_{ij}$ represent the Gram matrix for generating the performance form, respectively, with the weight parameters set to the same value for each layer [22].

### 2.3.2 Style migration

The style migration method based on generative adversarial network can realize the effect of high quality and controllable target style to some extent, but the computational efficiency is poor. In contrast, the style migration method based on generator model $G$ and discriminator model $D$ solves the problem of computational inefficiency to a large extent, i.e., it mainly optimizes the model [23].

In order to retain the advantages of generating a single style, generating multiple styles, and generating arbitrary styles for performance style migration, the fast style migration architecture is shown in Fig. 5, and its network architecture mainly consists of two parts, the transformation network and the loss network, in which the image transformation network is based on the residual network called as a residual network, and the stochastic gradient descent (SGD) is used for training, which is used to train the transformation network on a multi-typical performance clips dataset.

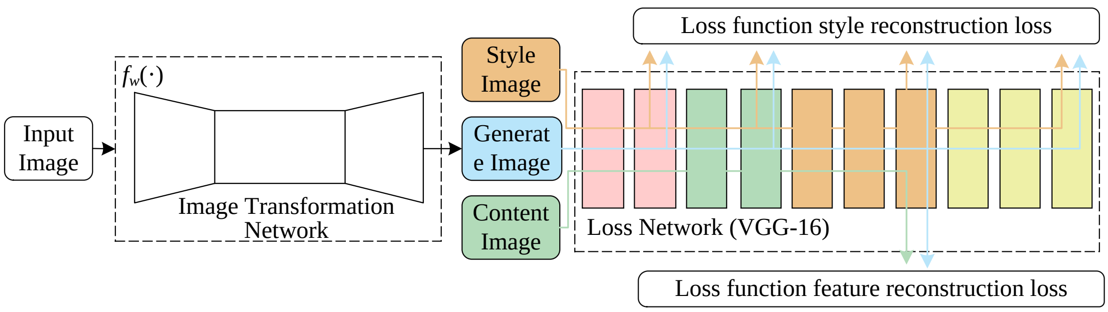



*Figure 5: Rapid Style Migration Architecture*

The weighted combination of its loss functions is denoted as:

$$L_{total} = \lambda_c L_{feat}(\mathrm{I}, \mathrm{I}_c) + \lambda_s L_{style}(\mathrm{I}, \mathrm{I}_s) + \lambda_{TV} L_{TV}(\mathrm{I}) \quad (8)$$

where $\lambda_*$ denotes the weight coefficients of each loss function, the performance feature reconstruction loss function $L_{feat}(\mathrm{I}, \mathrm{I}_c)$ denotes the Euclidean distance between the semantics of the lines, the style reconstruction loss function $L_{style}(\mathrm{I}, \mathrm{I}_c)$ is the squared Frobenius paradigm of the difference between the Gram matrices of the performance styles, and the fullvariance regularization serves as the artistic performance smoothing loss function $L_{TV}(\mathbf{I})$, to guarantee the spatial smoothness of the performance content. And $L_{FEAL}(\mathbf{I},\mathbf{I}_c)$ and $L_{style}(\mathbf{I},\mathbf{I}_s)$ constitute the perceptual loss function to measure the high-level emotional perception and semantic differences between performances.

The innovation of fast performance style migration compared to traditional style migration is the introduction of an end-to-end transformation network in the model, which is trained using deep features and combined with gradient backpropagation to adjust the network parameters to realize different transformation tasks, so that the generated performances have the stylistic characteristics of both the target style and the emotional style [24, 25].

The CIN process is shown in Fig. 6.The multi-style art style migration addresses the problem of excessive time cost of generating a single style by adding a set of $\gamma$ and $\beta$ parameters to IN for each style so that it is a $N \times C$-array,where $N$ is the number of styles being modeled, and $C$ is the number of output feature performance modes, and conditional instance normalization (ClN) is proposed so that it can learn multiple styles. Conditionalization $z$ of styles is performed as follows:

$$z = \gamma_s \left( \frac{x-\mu}{\sigma} \right) + \beta_s \tag{9}$$

where, $\mu$ and $\sigma$ are the mean and standard deviation of the feature image of the input layer taken on the spatial axes and the parameter vectors $\gamma_s$ and $\beta_s$ ,are obtained by selecting the rows corresponding to the indexed style labels $s$ in the matrices $\gamma$ and $\beta$.

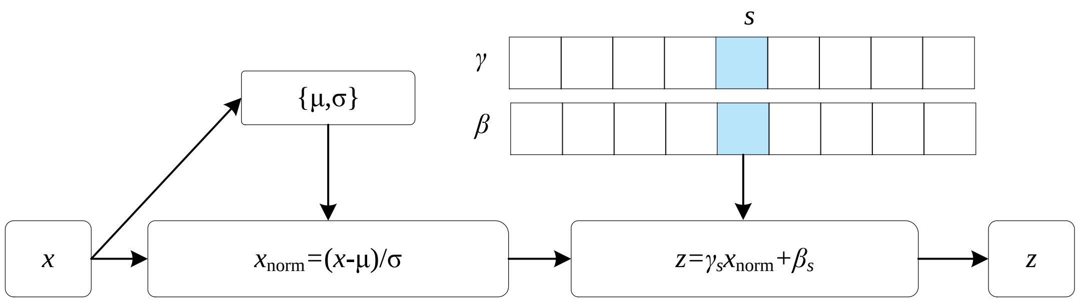



*Figure 6: CIN process*

The goal of CIN is to transform an activation $x$ of a layer into a normalized activation $z$ for style $s$, where all the convolutional weights of its network can be shared among many styles and it is sufficient to adjust the parameters of the affine transform after normalization for each style, where a set of $\gamma$ and $\beta$ represents a style. However, too many style types cannot be trained, as the network may become less efficient with increasing parameters in terms of content and style representation, and the results may lag behind.

In order to avoid the above problems a diverse performance style generation for deep generative feedforward networks is proposed, which can effectively synthesize multiple art forms in a single network and can generate new performance material by interpolation in the testing phase, where the new performance material is represented as a continuous embedding vector of one-hot selection units.

When constructing the new performance style loss function, it is found that the performance material generated directly using the Gram matrix has obvious artifacts and style element mixing problems, so it is proposed to improve the Gram matrix by using subtracting the mean before calculating the inner product between two activations, and its modified Gram matrix $\overline{G}_{ij}$, as well as the texture loss function $L_{texture}$ are as follows:

$$\overline{G}_{ij} = \sum_{k}(F_{ik} - \overline{F})(F_{jk} - \overline{F}) \tag{10}$$

$$L_{texture} = \left\| G_{gt} - G_{output} \right\|_1 \tag{11}$$

where $F_{*k}$ is the activation value of the vectorized $*$rd filter of the current layer of the loss network located at $k$, and $\overline{F}$ is the average of all activations in the current layer of the loss network. In order to measure the magnitude of the difference between the results of the same style under different noises, the diversity loss function $L_{texture}$ is added as follows:

$$L_{diversity} = \frac{1}{N}\sum_{i=1}^{N}\left\| \phi(P_i) - \phi(Q_i) \right\|_1 \tag{12}$$

where, $N$ is the number of input stylized sample targets $\{P_1, P_2, \cdots, P_N\}$, $\phi(*)$ denotes the features extracted from the Conv4 2 layer of the VGG network, $P_i$ is the $i$th output of the stylized sample targets, and $Q_i$ is equivalent to rearranging $P$. Based on the above, the stylization of the new performance material is completed.

# 3 Analysis of the application effect with the support of artificial intelligence

## 3.1 Experimental dataset and experimental configuration

The experiments in this paper use a database of multi-type performance clips as the training dataset and a professional style test dataset as the test dataset. The training dataset has about 50,000 performance clips, and each performance clip is scaled to 512×512, keeping the aspect ratio, and then randomly cropped to 256×256.The test dataset contains 50 groups of stylized performance control samples, each group of samples consists of the original performance clip and the stylized performance clip.The experimental environments are CUDA 11.2,cuDNN8. 0, ubuntul8.04 system, Tensorflow2.5. 0 deep learning framework, python3.8 programming language, NVIDIA Ge Force GTX 1080 GPU, 11GB graphics memory, data batch size set to 8, this paper uses Adam optimizer for training, network learning rate set to 0.0001. Figure 7 shows the experimental scene schematically. In order to verify the effectiveness of the style migration algorithm proposed in this paper in the actual teaching mode innovation, we choose to conduct experiments in the standard film and television teaching environment, the size of the experimental area is 5m×7m, a total of 165 reference points are set up, and the spacing between neighboring reference points is 0.5m.

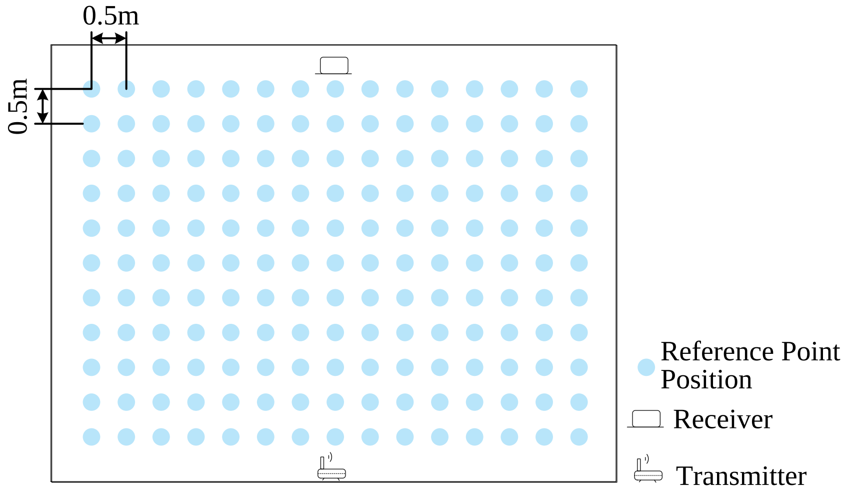



*Figure 7: Schematic of the experimental scene*

## 3.2 Algorithm performance validation

### 3.2.1 Impact of data pre-processing

In this paper, the style migration algorithm is selected to optimize the dataset, in order to evaluate the optimization effect, CNN model training and stylization test are carried out using the original data and the optimized data respectively, Table 1 shows the root mean square error of the style before and after the optimization, the root mean square error after the optimization of the style migration algorithm is lower than the optimization of the former by 0.06 points, and the root mean square error after the optimization of the former under AI-assisted teaching is lower than the optimization of the former by 0.16 points. The experiment proves that the noise existing in the original data does have an impact on the positioning accuracy, and the optimization processing of the collected CSI data can improve the performance style output accuracy to a certain extent, enhance the accuracy and stability of the style output, and provide technical support for the enhancement of the students' artistic expression.

*Table 1: Root mean square error of styles before and after optimization*

| Algorithm | Pretreatment status | Root mean square error/minute |
|---|---|---|
| Style Transfer Algorithm | Not pretreated | 0.21 |
| | Pretreated | 0.15 |
| AI-assisted teaching | Not pretreated | 0.36 |
| | Pretreated | 0.20 |

### 3.2.2 Effect of the number of samples generated

In order to verify the effectiveness of the style migration performance model proposed in this paper, 10 CSI magnitude samples are taken from each test dataset as the initial offline sample set, and the offline sample set is expanded to 200%, 200%, and 400% of the initial number, which is used as the training set of the CNN model, respectively, to compare the effect of the style output under the same test set. The results of the root mean square error are shown in Figure 8, from the initial score of 0.896, gradually reduced to 0.595, 0.432, 0.401, indicating that the style migration algorithm supported by artificial intelligence can improve the coherence of the generated performances, and provide technical support for the enhancement of students' artistic performance ability.

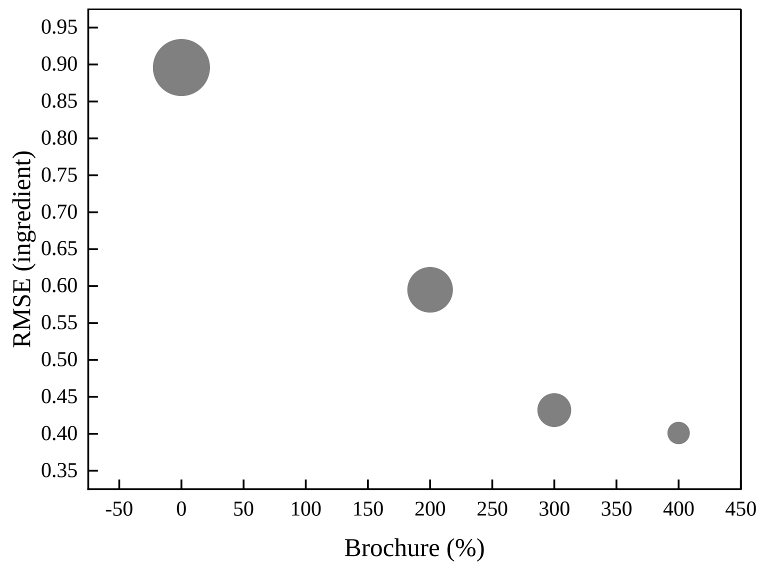



*Figure 8: Root mean square error results*

## 3.3 Validation of Teaching Effectiveness

### 3.3.1 Content consistency test

Using SPSS22.0 to correlate expert perception and audience perception, a large Spearman correlation coefficient was obtained, and Table 2 shows the consistency analysis of the overall sample. It is a significant positive correlation at the =0.01 level, which indicates that for the sample of this study, the experts gave a high level of evaluation for the new mode of performance, the core content reduction, the target emotional intensity and hierarchical communication coefficients are 0.865 and 0.842, and the coefficients of the consistency test for the role motivation and the behavioral logic are 0.798, which is greater than 0.750. However, the AI assisted teaching, the consistency ratings were 0.614, 0.565 and 0.702, which were lower compared to the style migration algorithm ratings. It can be assumed that the expert perception and the audience perception achieved better consistency, and the AI style migration algorithm of this study plays an important intermediary role in the enhancement of artistic performance, which can effectively narrow the teaching differences under different performance styles and promote the enhancement of students' artistic aesthetic ability.

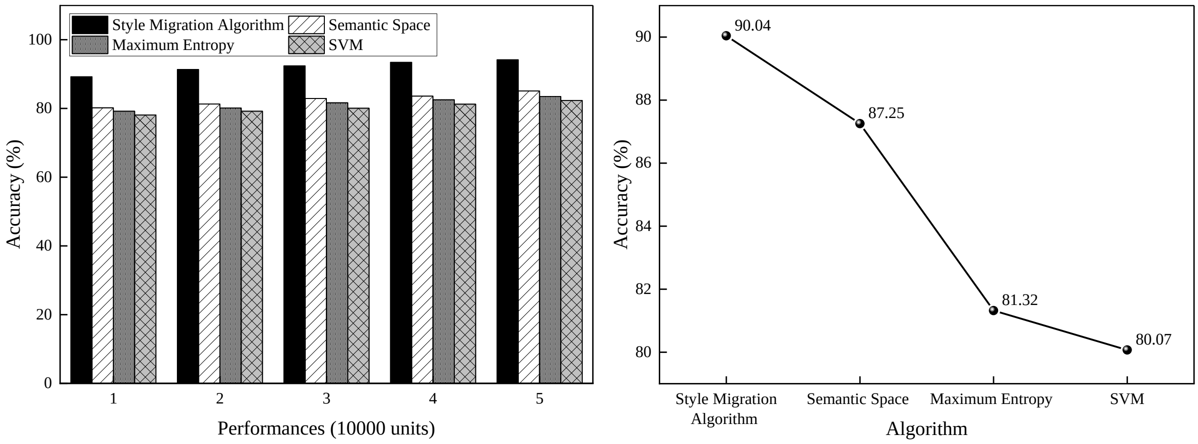
*Table 2: Consistency analysis of the overall sample*

| Assessment dimensions | Indicators | Algorithm | Coefficient value | p value |
|---|---|---|---|---|
| Correlation analysis | Core Content Reduction | Style Transfer Algorithm | 0.865 | 0.000 |
| | | AI-assisted teaching | 0.614 | 0.000 |
| Consistency test | Character Motivation and Behavioral Logic | Style Transfer Algorithm | 0.798 | 0.000 |
| | | AI-assisted teaching | 0.565 | 0.000 |
| Within-group correlation coefficient | Target Emotional Intensity and Levels of Communication | Style Transfer Algorithm | 0.842 | 0.000 |
| | | AI-assisted teaching | 0.702 | 0.000 |

### 3.3.2 Accuracy of emotional expression

In order to verify the effectiveness of the style migration algorithm supported by artificial intelligence in this paper, this section will compare and analyze the accuracy experimental results of the style migration algorithm and the traditional algorithm by using example verification. The experiments will test the accuracy of different algorithms separately, in which the traditional algorithm chooses maximum entropy model, semantic space and support vector machine.

The accuracy comparison will be conducted in two parts, and the accuracy comparison results are shown in Fig. 9. Fig. 9(a) shows the training set accuracy comparison, where 10,000, 20,000, 30,000, 40,000, and 50,000 performance clips are selected in the training dataset. The accuracy of this paper's style migration is higher than the traditional algorithm under any of the performance clips from 10,000 to 50,000, and the accuracy is about 9.1% higher than the best semantic space model in the traditional algorithm at the final 50,000 performance clips. Fig. 9(b) Comparison of the accuracy of the test dataset, where 50 sets of stylized performance samples are pooled and tested independently for accuracy under the style migration algorithm in order to make the experiment more convincing. It can be concluded that the accuracy of the style migration algorithm is significantly higher than other traditional algorithms, with an accuracy of 90.04%, which indicates that the algorithm can accurately extract the characteristics of film and television performances to make the students' artistic performance more convincing.




(a) Comparison of training set accuracy (b) Accuracy of the test dataset

*Figure 9: Comparison of accuracy results*

### 3.3.3 Style Recognition

In order to avoid data isolation phenomenon, the style recognition before and after the application of the algorithm was evaluated using expert ratings and audience perception, and the style recognition scores are shown in Table 3.Under AI-assisted teaching, the expert ratings of the target performance style features and the integration of the human style with the target style were (7.8±1.0) points and (8.1±0.5) points after the application of the expert ratings and audience perceptions. The style migration algorithm was (4.4±0.7) points before application and (9.1±1.4) points after application on the expert score of the target performance style features. For the integration of personal style and target style, the audience perception was (6.4±0.8) points before application and reached (8.8±0.9) points after application. It shows that the style migration algorithm can make the generated film and television performance style more prominent, not only strengthening the personal style, but also retaining the original artistic style, realizing the organic fusion of artificial intelligence and artistic performance, proving that artificial intelligence support can effectively improve the teaching effectiveness of artistic performance and the ultimate stage infectiousness.

*Table 3: Style recognition scores*

| Indicators | Before application | | After application | |
|---|---|---|---|---|
| | Style Transfer Algorithm | AI-assisted teaching | Style Transfer Algorithm | AI-assisted teaching |
| Target Performance Style Characteristics Expert Ratings | 4.4±0.7 | 3.1±0.6 | 9.1±1.4 | 7.8±1.0 |
| Personal Style Integration with Target Style Audience Perception | 6.4±0.8 | 5.3±0.6 | 8.8±0.9 | 8.1±0.5 |

# 4 Conclusion

This paper collects film and television works based on generative adversarial network, constructs style database, and realizes artistic evaluation by combining style migration. The multi-type performance clip database is used as the training dataset, and the professional style test dataset is used as the test dataset. The results of algorithm performance validation show that the root mean square error of the style migration algorithm after optimization is 0.06 points lower than that before optimization, and the root mean square error gradually decreases from 0.896 points to 0.401 points. In the consistency test, the logical coefficient of character motivation and behavior is 0.798, which is greater than 0.750, proving that the expert perception and the audience perception have consistency. The training set comparison results show that the accuracy of the style migration algorithm is about 9.1% higher than the best semantic space model in the traditional algorithm. Comparison of the accuracy of the test data set found that the accuracy of the style migration algorithm is 90.04%, which can effectively improve the students' artistic expression ability. The integration of artificial intelligence technology with film and television teaching can innovate the form of performance and promote the comprehensive development of film and television performance education in the direction of intelligence as well as personalization. In the future, more models and algorithms will be integrated to deliver high-quality talents for the intelligent transformation of the film industry, help the artistic expression form toward diversified development, and inject a steady stream of innovative power for the sustainable development of the film and television industry.

# About the Author

Song Song, female, was born in 1985 in Shandong Province, China. She received her Master's degrees from Shandong University of Arts and the New York Film Academy in the United States, respectively. Currently, she works at the School of Fashion Communication, Beijing Institute of Fashion Technology. Her main research interests include: research on directing and performing arts in traditional Chinese theater and opera, filmmaking, and innovative studies on cultural narrative in the intelligent era.

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