Research on Digital Media Art Innovation Model Based on Convolutional Neural Security Network

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Abstract: As a professional system that intersects technology, humanities, and art, digital media art occupies an important position in the art category. With the continuous advancement of information technology, the opportunities and challenges faced by digital media art education have not only brought about changes in digital media art education, but also have a certain impact on the ecological relationship of art design. This paper takes public art as the starting point, analyzes the practical cases related to digital media art at home and abroad, sorts out and summarizes the current digital media art teaching status, based on the method of convolutional neural network, further explores the suitable digital media from the perspective of education and teaching mode Innovative methods for the art profession.

Key-words: Digital Media Art; Public Art; Convolutional Neural Network; Innovative Method

1 INTRODUCTION

The Digital Media Art major focuses on the cultivation of students' comprehensive abilities, such as innovative thinking models, professional technical capabilities, and solid design foundations. This kind of professional ability is the objective requirement of the current social public environment, and it is also the training goal of college art education. As we all know, the establishment of digital media art majors in my country's universities is short, leading to the majority of the teaching of this major in the stage of exploration and development. Especially in the current situation where some colleges and universities have insufficient teachers, imperfect hardware facilities, and fail to closely integrate with digital development, most of the digital media art education still continues the traditional teaching mode. At present, this kind of education situation cannot provide the driving force for the development of the "cross-integration" of public art and digital media art.

First of all, as a cross-discipline, the digital media art major aims to cultivate comprehensive and comprehensive talents that combine art and technology. However, due to the lack of systematic and cross-cutting teaching mode, the students of this major failed to form a systematic cross-thinking and could not meet the goal of compound talent training. Secondly, the digital media art major pays more attention to theoretical teaching under the traditional education model, and is slightly insufficient in the cultivation of practical ability. Of course, this aspect is limited by objective reasons such as the short development time of the discipline.

On the other hand, the teaching practice related to art is deeply affected by the iteration of technological development, and the digital media art education practice of universities is not at the forefront of development of industry. Therefore, although some colleges and universities have a certain practical teaching environment, compared with the industry, the results and levels of practical teaching are uneven, and it is impossible to establish a virtuous circle teaching mode that combines theory and practice.

In addition, the digital art major is a cross-combining field of technology. Its development must not only rely on the support of technology, but also adapt to the expression of artistic language. Colleges at home and abroad are based on their own disciplines and resource advantages. Focus on the development direction. Although the development of digital technology and artistic creation differ in language, which has promoted a variety of innovative practices in the field of digital media art education, the relevant professional fields of domestic and foreign universities have not yet a unified and perfect education and teaching model has been established, and it is still in the process of continuous exploration and practice.

Digital media art was born at the end of the 20th century. It is an emerging field that accompanies the combination of digital technology and art. my country's digital media art professional teaching was born in the late 1980s, when some universities in our country had already launched the research and exploration of computer graphics technology. With the advent of the 21st century, digital media art has attracted widespread attention from the academic and educational circles in my country. Some universities followed the trend of the times and established digital media arts or related majors according to their own characteristics. According to the record of the ministry of education, between 2000 and 2004, China successively opened 11 colleges and universities specializing in digital media arts or related technologies. In 2008, the Ministry of Education registered 32 colleges and universities that added digital media arts or related technology majors. As of the end of 2009, the ministry of education had registered or approved 150 universities that approved digital media arts or related majors. Polytechnic independent colleges have become mainstream groups for setting up related majors, and colleges and universities have successively gotten involved in this field. In particular, almost all post and telecommunications and information colleges have set up digital media arts or related majors. It can be seen that the most significant feature of the current digital media art professional teaching is that the science and engineering and independent colleges occupy the main body of the professional education. In addition, normal schools and comprehensive colleges are also the main groups that offer this major. In comparison, art media colleges and junior colleges offer fewer programs for this major.

Based on actual research, the author summed up the main directions of the digital media art teaching reform that learns from each other's strengths, complies with each other, and integrates diversity to construct innovative teaching thinking. Students in science colleges have good logical thinking skills, while students in art colleges are good at creativity and have strong hands-on skills. Therefore, in order to improve the employability of students in cross-fields, it is advisable to adopt cross-platform and cross-professional teacher teaching and resource sharing methods to enhance students' comprehensive quality and ability. For example, the teaching platform of the digital media art major can take a more diversified approach. The faculty of media art and animation teaching can reach a resource sharing model with the college's visual communication, public art, music creation and other majors. This paper takes public art as the starting point, analyzes the practical cases related to digital media art at home and abroad, sorts out and summarizes the current digital media art teaching status, based on the method of convolutional neural network, further explores the suitable digital media from the perspective of education and teaching mode Innovative methods for the art profession.

2 LITERATURE REVIEW

The design of convolutional neural networks is inspired by the structure of the mammalian visual system. Hubel and Wiesel proposed a visual structure model based on the cat's visual cortex in 1962[1]. The small, overlapping visual areas where these neurons can feel light are called receptive fields. These neurons play the role of local operators in the input space, and more complex neurons have a larger receptive field. In 1980, Fukushima proposed the first hierarchical structure organization Neocognition that can be used to process images. This organization uses local connections between neurons. Fukushima pointed out that the network can be translationally invariant. In 1988, Convolutional Neural Networks were used by Toshiteru Homma et al. to identify spatiotemporal bipolar patterns[2]. Yann. LeCun et al. also used convolutional neural networks for handwritten font recognition and text recognition tasks [3, 4]. Its particularity is reflected in the following three aspects:

1. According to characteristics of local receptive field of simple cells in the primate visual system, neurons in the adjacent two layers Partial connection is used instead of full connection.

2. To reduce the required training parameters, weight sharing is adopted.

3. Using sub-sampling operations to simulate the functions of complex cells in the primate visual system, making the network more robust, while achieving the purpose of dimensionality reduction and preventing overfitting. Based on the above characteristics, the convolutional neural network has a high degree of non-deformation against translation, zoom, tilt and other forms of deformation, and has been widely used in postal code recognition, license plate recognition and face recognition.

In 1980, Fukushima proposed a multi-layer artificial neural network called Neocognitron. The network structure is composed of many S layers and C layers alternately, and very sparse local connections are used between layers. This network is also considered to be the prototype of a convolutional neural network. The model has no deformation for slight scaling and rotation of the data, but at that time there was no supervised learning algorithm to train it.

In 1998, LeCim et al. [3] proposed the well-known LeNet-5 convolutional neural network, which uses local connection, weight sharing and sub-sampling operations at the same time, so that the network has a certain degree of translation, scaling, and rotation invariance. The LeNet-5 convolutional neural network is also considered to be a true convolutional neural network.

Sermanet et al. [11] combined the outputs of the first sub-sampling layer, and sent them to the classifier as the final feature. The motivation for using the above strategy is that the features output by the second sub-sampling layer contain more global information and have stronger invariance, but lack local detail information, while the features output by the first sub-sampling layer contain more Partial detail information, but lacks a certain degree of invariance. Combining the features of the two stages to obtain multi-scale features makes the classifier easier to classify.\

In 2012, Krizhevsky and others used a convolutional neural network to win the first place in the ILSVRC competition with far better results than the second place. The convolutional neural network uses ReLU as the activation function. Many studies [12-13] have shown that ReLU increases the negative activation value to 0, which can produce sparse representation, and when the gradient descent method is used for training, its the convergence speed is faster than the hyperbolic tangent function and the sigmod function. The convolutional neural network also uses drip [14] to prevent over-fitting and improve test accuracy.

Although large-scale convolutional neural networks perform very well in classification tasks, there is no in-depth research on why convolutional neural networks have such excellent performance and how they can be improved. In 2014, Zeiler et al. [15] used the deconvolution method [16] to visualize the weights of the intermediate layer and the classifier to solve the above two problems. Using this method, Zeiler et al. explored and proposed a network structure superior to Krizhevsky et al. The classification accuracy in the ImageNet classification data set is better than the latter.

In the past few years, researchers have spent considerable effort to design suitable feature extractors. For example, some recognition system structures use a single-layer feature extractor, and then add a classifier trained by a supervised method. Typical applications are SIFT (Scale Invariant Feature Transformation) [23,24], hOG (Histograms of Oriented, Gradient Bts, etc.) and Geor[25,26] in recent years. Inspired by the hierarchical characteristics of the animal-like visual cortex [27], but more importantly, studies have shown that the hierarchical model is better than the single shallow target recognition method [28]. Therefore, the research on the hierarchical model is increasing. more. Among them, there are more and more researches on the structure of convolutional neural networks.

In [29], a hybrid neural network composed of a convolutional neural network and a support vector machine is used to combine the advantages of the convolutional neural network's easy learning to invariant features and the SVM's easy learning to determine the plane. The supervised learning method has achieved an error rate of 5.9% on the NORB dataset. In, the "pseudo-taks" automatically generated under unsupervised conditions are used to supervise the training of the hierarchical model, so that the neural network obtained by training has stronger generalization and can adapt to more tasks. In [31], although the final structure is also a convolutional neural network, it uses a layer-by-layer unsupervised learning method to avoid a series of problems such as too many training parameters for the supervised learning algorithm at one time. In [32], the neural network structure is a sparse deep-belief neural network composed of two-layer sparsity-restricted Boltzmann machines. The author uses the fast deep-belief network learning method proposed in [33] in 2006, first layer by layer Unsupervised learning, after the completion of the global fine-tuning method to determine the final parameters. There are also articles in the hierarchical model, based on prior knowledge, using artificially designed Gabor filters in the first layer, and using unsupervised training methods in the second layer. The typical articles in this area include, etc., the Gabor filter. The alternative is a directional edge detection filter, such as a gradient operator, including SIFT and HOG. This type of model is called the HMAX-type structure. The improvement in this structure is to pass Gabor through unsupervised training to obtain a Gabor-like edge operator.

3 CONVOLUTIONAL NEURAL NETWORK THEORY

3.1 NEURONS AND ACTIVATION FUNCTIONS

The structure of neural network is inspired by neuroscience. By simulating the form of biological neuron, it plays the role of layer-by-layer feature extraction through layer by layer. The depth is usually used to represent the chain of model layers. Therefore, the method of data analysis and mining using neural networks is also called deep learning. The method of deep learning is usually to solve the difficulties encountered in fitting complex mapping relations. Each neural network represents a broad family of functions, and through the selection and design of the network structure, people can add prior knowledge to limit the scope of the mapped function family. Therefore, the neural network has more flexible adjustment methods and strong adaptability, which makes it make good progress in many fields [45].

The basic unit of a neural network is a neuron. For a single neuron, it is composed of several inputs combined with an activation function, which can be expressed as

$$y = g\left(w^T x + b\right) \tag{3.1}$$

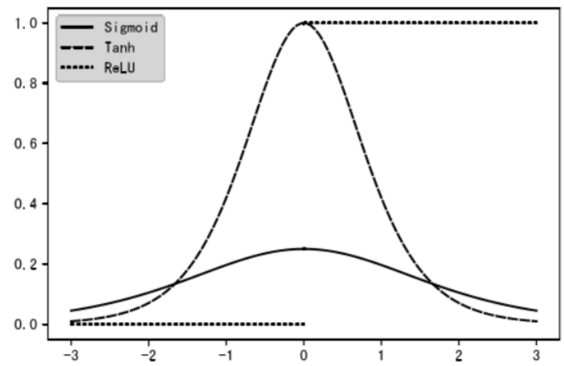
Where $g\left(x\right)$ represents the activation function mapping. The three most common activation functions are $\mathrm{Re}LU$, $Sigmoid$ and Tanh, and their expressions are

$$\mathrm{Re}LU\left(x\right) = \max\left(0, x\right) \tag{3.2}$$

$$\sigma\left(x\right) = \frac{1}{1+e^{-x}} \tag{3.3}$$

$$\mathrm{Tanh}\left(x\right) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{3.4}$$

Their function and derivative images are shown in Figure 2.2. It is not difficult to see that the derivative form of $\mathrm{Re}LU$ is very simple. For the active unit, the derivative is constant at 1, and there is no second derivative, which makes it easy to optimize in the process of backpropagation. Therefore, most convolutional neural networks choose to use as the activation function. However, the activation function cannot activate the inactivation zone that is not in the activation value through backpropagation. Some researchers use Leaky $\mathrm{Re}LU$ to set the slope of the negative $\mathrm{Re}LU$ area to a smaller value α or on this basis use a parameterized rectified linear unit ($P\mathrm{Re}LU$) to automatically learn negative the slope of the value area. $Sigmoid$ and Tanh functions have similar problems. They are not sensitive to changes in the input when they are in the saturation region. From the derivative image, when the two are in the saturation region, the derivative is close to 0, which will also bring back propagation. difficulty. Relatively speaking, the Tanh activation function is better than the $Sigmoid$ function, because in the region close to 0, its derivative value is 1, and it is not easy to cause the gradient to disappear. In recurrent neural networks such as LSTM, Tanh is used as the activation function. In some cases, such as convolutional gated neural networks [46], the $Sigmoid$ function is used as a gate to select the input.



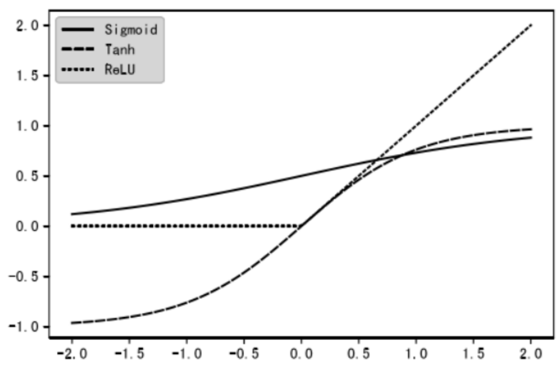


Fig.1. Common activation functions and their derivatives

If each output neuron is only to the input neuron, the neural network is a feedforward neural network. On this basis, if each output neuron is connected to all input neurons, it is a fully connected neural network. Each layer of the feedforward neural network can be expressed as

$$y = g\left(W^T x + b\right) \tag{3.5}$$

3.2 CONVOLUTIONAL NEURAL NETWORK

In terms of logical structure, recurrent neural networks can better extract sequence features. However, some studies have shown that recurrent neural networks cannot do too long sequences. To make the most of information. In addition, the structure of RNN makes it difficult to parallelize processing, which makes the training and inference process take a lot of time. On the other hand, the convolutional neural network has also shown its ability to not lose to the recurrent neural network in text classification and speech reconstruction.

A convolutional layer consists of three modules: convolution, activation and pooling, as shown in Figure 2.

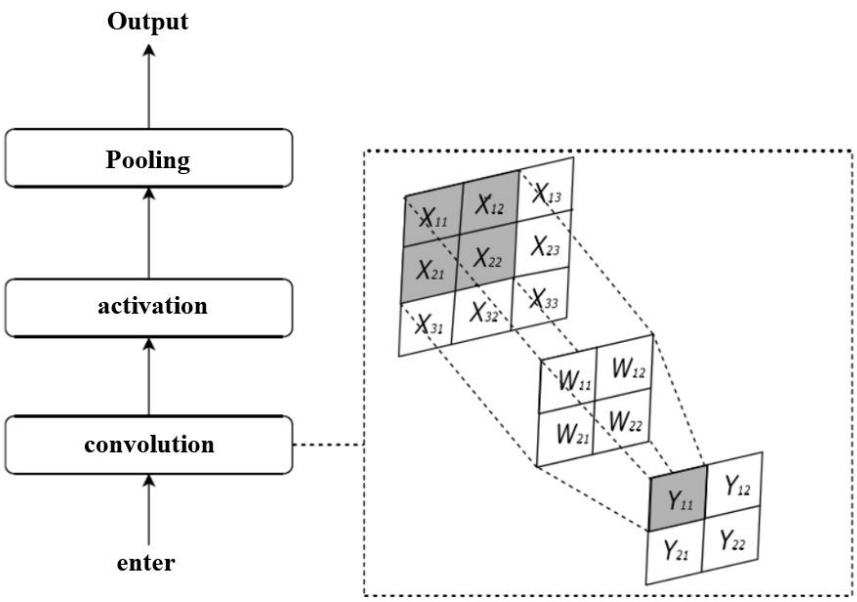


Fig.2. Basic technical mechanism of convolutional layer

The activation layer is the same as the activation of neurons. Almost all of the convolutional networks use $\mathrm{Re}LU$ and its variants as the activation function. The most important part of a convolutional layer is module. Since the weights are automatically learned by the network, the convolution in the convolutional neural network actually performs mathematical and signal analysis. Related operations in. That is, for Y_1 in the figure, its value is

$$Y_1 = W_{11} * X_{11} + W_{12} * X1_2 + W_{13} * X_{13} + W_{14} * X_{14} \quad (3.6)$$

In practical applications, it is difficult for a single convolution kernel to fully extract features, so multiple convolution kernels are used for convolution operation, which also makes the convolution kernel need to add a channel layer to match the dimensionality of the input data. For convolution with a channel layer, each channel of the convolution kernel performs a convolution operation on each channel of the input feature and then sums it as the final convolution result.

The pooling layer is used for down-sampling information within a certain range, with the purpose of extracting meaningful information and increasing the receptive field of the next layer of network. Pooling is generally divided into maximum pooling and average pooling. The maximum value in a certain range and the average of all values are selected and passed to the next layer. Maximum pooling can better extract useful feature parts, and average pooling can better optimize parameter weights when backpropagating. Some researchers also use global maximum pooling at the end of the network to summarize the information of the entire channel and directly use it as the output of the network.

3.3 NETWORK LOSS FUNCTION AND BACK PROPAGATION

Once the structure of the neural network is determined, its parameters map the input to the output result and form a distribution $p_{\mathrm{mod}el}\left(y|x;\theta\right)$. Using the principle of maximum likelihood, it can be obtained that for classification tasks, the $Soft\max$ function is used to normalize the output of the neural network to a probability output, and the use of cross entropy as the loss function can be a good measure of the data distribution of the model output and the distribution of the training set the difference is expressed as follows

$$J\left(\theta\right) = -IE_{x,y \sim \hat{p}_{data}} \log p_{\mathrm{mod}el}\left(y|x;\theta\right) \quad (3.7)$$

Since the neural network corresponds to a high-dimensional non-convex optimization problem, the optimal solution cannot be found. The partial derivative and chain rule can be used to weight and sum from the loss function step by step to the input. Hidden layer gradient calculation, this method is also vividly called back propagation. For the convolutional neural network, the gradient of the output to the loss function is δ^l, the forward propagation result of the input is z^{l-1}, the loss function is δ^{l-1}, the convolution kernel is W^l, and the input result without activation function is a^{l-1}. Then there is

$$\delta^{l-1} = \left(\frac{\partial z^l}{\partial z^{l-1}}\right)^T \delta^l = \delta^l * rot180\left(W^l\right) \odot \sigma'\left(z^{l-1}\right) \quad (3.8)$$

$$\frac{\partial J\left(W,b\right)}{\partial W^l} = a^{l-1} * \delta^l \quad (3.9)$$

The purpose of backpropagation is to calculate the gradient of all weights to the loss function, and perform the change operation on the gradient through the optimizer to complete the update of the weight. Common optimizers include $SGD, Momentum, Adam$ and so on.

3.4 CONVOLUTIONAL NEURAL NETWORK

3.4.1 Neural network

First introduce the neural network. For details of this step, please refer to Resource 1. Brief introduction. Each unit of the neural network is as follows:

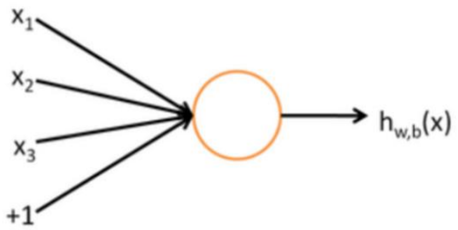


Fig.3. Neural Description

The figure below shows a neural network.

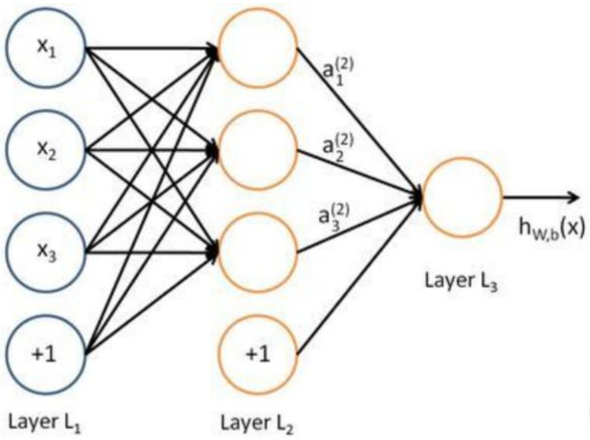


Fig.4. has a neural network of implicit layers

3.4.2 Convolutional Neural Network

Inspired by Hubel and Wiesel's research on the electrophysiology of cat visual cortex, someone proposed a convolutional neural network (CNN).

Convolutional neural network consists of three parts. The first part is the input layer. The second part consists of a combination of convolutional layers and pooling layers. The third part consists of a fully connected multilayer perceptron classifier.

3.4.3 Local receptive field

The convolutional neural network has two artifacts that can reduce the number of parameters. The first artifact is called the local perceptual field. It is generally believed that people's cognition of the outside world is from local to global Therefore, each neuron doesn't actually need to perceive global image, and only requires local perception, then at a higher level of integration of local information, get the idea of global information network connections is also inspired by biology vision system structure Neurons in the visual cortex local receive information (that is, these neurons respond to certain areas of stimulation only) As shown below: Full connection on the left, partial connection on the right.

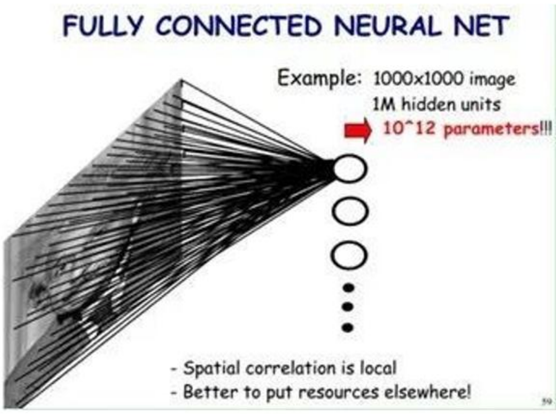


Fig.5. full connection diagram

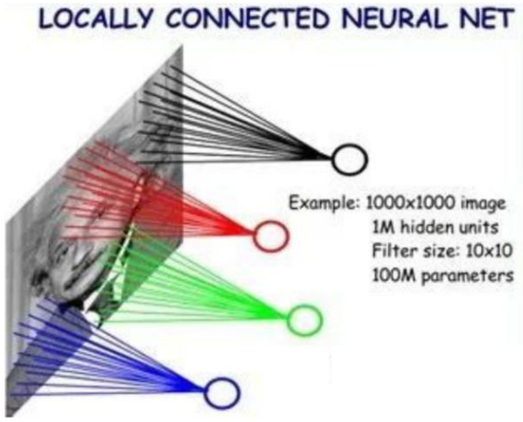


Fig.6. Partial connection diagram

In the upper right figure, if each neuron is only connected to 10×10 pixel values, the weight data is 1000000×100 parameters, which is reduced as one of the original. The 10×10 parameters corresponding to the 10×10 pixel values are actually equivalent to convolution operations.

3.4.4 Multi-volume nuclear

Only 100 parameters described above, indicate that only 1 10 * 10 convolutionary, obviously, the feature extraction is insufficient, we can add multiple convolutionary cores, such as 32 volumes, you can learn 32 feature. When there is a plurality of conjunctions, as shown below:

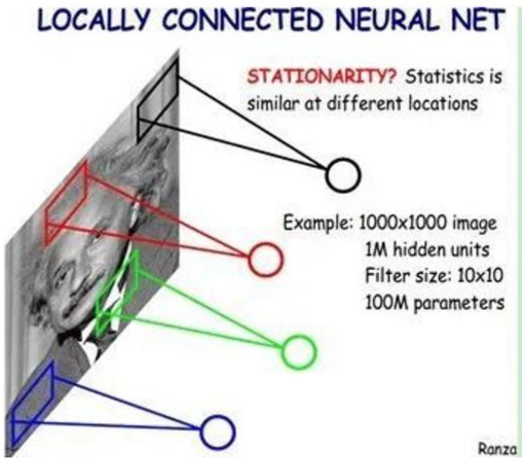


Fig.7. Multiple convolutionary cores（1）

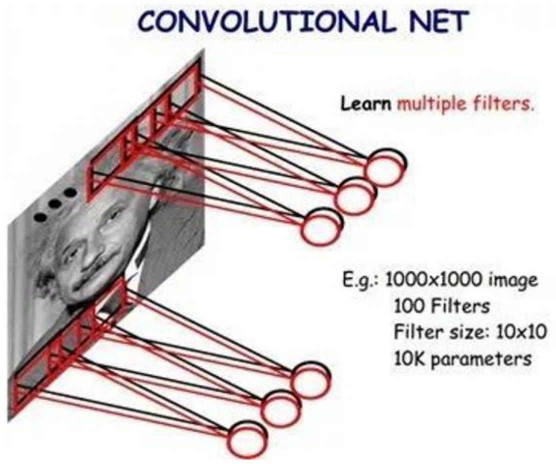


Fig.8. Multiple convolutionary cores（2）

On the right, different colors indicate different convolutionary nuclear. Each volume will be generated to another image. As shown in the figure below, the figure below has a small error, so that $w1$ is changed to W0, and $w2$ can be changed to $w1$. They are still called them in $w1$ and $w2$.

The figure below shows the convolution operation on the four channels, there are two convolutions to generate two channels. It should be noted that each passage corresponds to each passage on the four channels, first ignore $w2$, only $w1$, then the value at a location (i, j) at $w1$, is on four channels (The convolution result at (i, j)) is added then then the activation function is worth it.

$$h_{ij}^{k} = \tanh\left(\left(W^{k} * x\right)_{ij} + b_{k}\right)$$

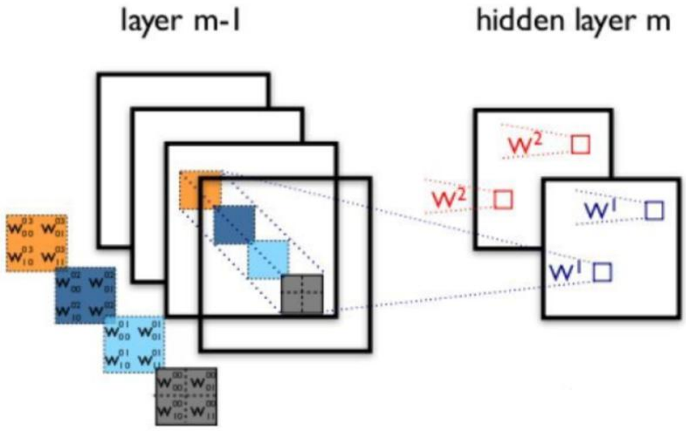


Fig.9. Convolution operation on four channels

Therefore, in the process of obtaining 2 channels by convolution of 4 channels in the above figure, the number of parameters is 4×2×2×2, where 4 means 4 channels, the first 2 means generating 2 channels, and finally the 2×2 represents the size of the convolution kernel.

3.5 INNOVATIVE DIRECTION OF DIGITAL MEDIA ART EDUCATION AND TEACHING PRACTICE

1. Build a professional ecosystem and cultivate interdisciplinary innovative design concepts as a new direction in the art category, the major of digital media art is closely related to social development. To cultivate high-quality professional talents, it is not enough to rely solely on the students' own interests. The most important thing is the cultivation of innovation ability by the school and the society. Public art closely follows the development of the times and is closely related to social innovation and social progress.

In order to cultivate the innovative design concept of digital media art more systematically, Mr. Zhou Yue and Technology proposed innovative methods for the training model of the professional's innovative ability. The four aspects of ecology build an ecological circle belonging to the major of digital media art, and establish a solid foundation for innovative design concepts. To build a professional ecosystem, we should fully understand the connotation of discipline construction and respect the laws of education. It is not only necessary to clarify the relationship between disciplines, majors, courses, teaching materials, and teachers, and to seek a benign ecological development of art education, but also to focus on improving the internal ecology and artistic ecology of education and implement ecolo-gicalization with the background of social ecology and technological ecology.

In the process of building a professional ecosystem, attention should be paid to the balance between internal ecological construction and external ecological construction. The external ecosystem provides the basic necessary conditions for the internal, the internal ecosystem is the professional content of the external perfect system; the political consciousness ecology such as national policies, professional orientation, and social mainstream values is the core advantage of the external ecosystem; in the process of building the internal ecosystem It should make full use of the rigid conditions provided by the external ecosystem to build the internal ecosystem, focus on innovating the internal ecological mechanism, and establish an internal ecosystem with systematic professional attributes, innovative knowledge structure, and advanced ideology. The combination of internal and external, interdependence, can provide an innovative professional ecosystem for the digital media art education model, and lay a solid foundation for cultivating the innovative design concepts of students of this major.

2. Transform the traditional education space and establish an innovative practice space the traditional digital media art professional education model is biased towards theoretical teaching, ignoring the cultivation of students' practical ability. The development of the future society will inevitably require more talents who combine innovative design and technology applications. This requires the school to set training goals according to its own educational basic conditions, and establish innovative practice spaces based on the training goals to meet the space needs of the professional teaching. The establishment of innovative practice space allows students to start from their own innovative design capabilities, combine diversified practical applications,

cultivate professional capabilities, and contribute their own strength to future social development.

In the future, the relationship between design, art, and technology will become closer and closer, and the requirements for the training of talents in universities will become higher, and requirements for education model of various colleges and universities will become more and more stringent. Schools with good systematic professional resources can quickly build innovative platforms for students, so that students' innovative abilities can be applied on the practical platform. However, because some colleges and universities do not have enough professional and teaching resources to provide students with innovative practice space, they can consider cooperating with social institutions or related laboratories to inject social vitality into school educational resources. This method not only allows students to understand the future social needs, but also provides infinite possibilities for the future through innovative practice spaces.

3. Introduce interdisciplinary fields to empower the cultivation of interdisciplinary talents The future space is a public space composed of people, media, and the environment. The composition of the space will bring innovative changes to the design of the future and the educational model. The digital media art major has the characteristics of fusion and innovation, and the continuous pursuit of innovation and change is the typical form of the major. The goal of this major is to cultivate compound talents. It should combine the current innovation characteristics and environment, integrate multiple disciplines to participate in cooperation, and innovate the professional education model, which is Cultivate empowerment. When innovating the digital media art education model, we should take the initiative to use the advantages of different faculties to complement each other, and have innovative educational thinking that integrates across borders. For example, students majoring in engineering digital media art are good at logical thinking and have greater advantages in software programming, big data collection, and software application practice, while students majoring in digital media art have greater advantages in performance, animation, design, and literature. Advantage. Cross-platform, cross-professional teacher integration and resource sharing can be adopted, and to focus on the simultaneous development of horizontal and vertical scientific research. Cross-discipline not only pays attention to the cross-discipline, but also pays more attention to the cross-content. Such as cross-application of knowledge, cross-professional cooperation, cross-discipline discussion, cross-industry running-in, etc., all take "innovation" and "cooperation" as opportunities. The injection of interdisciplinary subjects not only empowers the cultivation of compound talents in this major, but also promotes the in-depth development of the digital media art major.

4. Deeply integrate industry resources and build an innovative professional collaboration resource library Due to the small number of domestic colleges and universities offering digital media arts majors, the professional education resources of each college are limited, which cannot meet the multi-faceted resource needs of students. Therefore, domestic universities can share existing resources, integrate resources between different universities, strengthen university cooperation, promote university education model innovation, and provide a rich professional and innovative resource library for digital media art education models. Deep integration of resources requires full consideration of China’s transformation and upgrading, integrated development of intelligence The demands of the energy-efficient era add connotations to the construction of an innovative resource pool. Some colleges and universities can cooperate with outstanding social enterprises or institutions to integrate and innovate open resources, optimize educational resources, and promote innovation in educational models.

4 CONCLUSION

With advancement of information technology, the opportunities and challenges faced by digital media art education have not only brought about changes in digital media art education, but also have a certain impact on the ecological relationship of art design. This paper takes public art as the starting point, analyzes the practical cases related to digital media art at home and abroad, sorts out and summarizes the current teaching status, on the method of convolutional neural network, further explores the suitable digital media from the perspective of education and teaching mode Innovative methods for the art profession. With the continuous advancement of science and technology today, digital media art, as an emerging profession in the era of science and technology, integrates the characteristics of art, design, and technology, and provides a direction for promoting the innovative development of the public environment in the future. The innovation of digital media art education teaching practice model is based on the future social development trend and scientific and technological support, through the construction of professional ecosystems, creation of practice spaces, introduction of interdisciplinary, integration of teaching resources and other methods, to build an innovative education for digital media art majors model. From the perspective of public art, the innovation of digital media art education model provides impetus for the integration and development of digital media art and public art, and has a positive impact on the innovative development of art in public spaces in the future.

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