Chapter 17
Electronic Information Image Processing Technology Based on Convolutional Neural Network

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Abstract Under the background that modern information technology and the Internet are closely related to people's lives, deep learning algorithm based on convolutional neural network has important application significance in image processing. At present, the development of the top science and technology in various industries in society is often related to artificial intelligence, convolutional neural network algorithm applied to electronic information image processing provides a means and approach for artificial intelligence, and it has been widely used for image analysis in the medical field. The fields of intelligent recognition in computer systems and even image restoration in criminal investigation have contributed to the development of high-quality scientific and technological life in modern society. Based on the above background, this article gives a brief introduction to the related technologies of convolutional neural network applications and electronic information image processing. I hope that those who are interested in research in the related fields will have some knowledge.

17.1 Research Status

In 1994, LeNet was born as the earliest convolutional neural network promoting the development of deep learning. After many successful iterations, Professor Yann LeCun proposed in the paper Gradien-based learning applied to document recognition in 1998. It is the first convolutional neural network successfully applied to digital recognition problems, on the MNIST dataset. LeNet-5 can achieve an accuracy rate of about 99.2% [1].

In 2012, AlexNet implemented by Professor Alex Krizhevsky won the championship in the Image Classification Competition (ILSVRC) organized by ImageNet

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R. Kountchev et al. (eds.), *New Approaches for Multidimensional Signal Processing*, Smart Innovation, Systems and Technologies 216,
https://doi.org/10.1007/978-981-33-4676-5_17

[2]. AlexNet successfully applied tricks such as ReLU, Dropout, and LRN in CNN for the first time.

It avoids the negative effects of increasing the number of network layers in order to obtain better training results. For example, overfit, gradient disappearance, gradient explosion, inception proposed another angle to improve the training effect, the convolutional layers are combined together in a parallel manner to make more efficient use of computing resources and obtain more features under the same amount of calculation [3].

In 2014, the Visual Geometry Group (VGG) model ranked second in ImageNet Large-Scale Visual Recognition Challenge (ILSVRC), second only to GoogLeNet, but the VGG model performed better than GoogLeNet in multiple transfer learning tasks [4]. Moreover, VGG model is the preferred algorithm to extract convolutional neural network (CNN) features from images.

In 2015, in order to solve the downgrade problem, Dr. He Kaiming adopted a deep-level residual learning framework to solve the problem of reduced accuracy. Studies have shown that these residual networks are easier to optimize and accuracy can be obtained by increasing depth. This residual network reached an error of 3.57% on the ImageNet test machine and became a champion in the mission of ILSVRC 2015 [5].

17.2 The Principle of Convolutional Neural Network

17.2.1 Local Receptive Field

The convolutional layer neurons and the neurons in the preceding layer are not fully connected. In the actual algorithm, neurons connect with a small part of the neurons in the previous layer to communicate data and information. In convolutional neural networks, the area between neurons and neurons is the local receptive field. This model mainly refers to the structure of biological neural networks in nature [6].

Because the biological neural network performs information transmission between neurons, a neuron only needs to be connected to a small part of other neurons, the application of this structure in the neural network is actually considering that the spatial correlation between adjacent pixels in the electronic information image can be fully utilized. It can greatly reduce the number of samples that the system needs to select for image processing, so as to reduce the time required for image processing, reduce the CPU performance requirements for image processing, and achieve better adaptability of image processing technology in different computer systems [7].

17.2.2 Weight Sharing

Each neuron of a convolutional layer in a convolutional neural network has both a partial value and the weight of the local receptive field. In the application of convolutional neural network algorithm, let each neuron have the same bias and weight. The same neuron bias and weights for this entire neural network are called convolution kernels. In using convolutional neural network algorithms, neurons use the same convolution kernel to convolve with neurons in the previous layer. In this way, regardless of the number of neurons, the number of models that need to be trained has always been kept on the same convolution kernel. Therefore, the feature of weight sharing in convolutional neural network is mainly to reduce the number of parameters used in model training, which is beneficial to reduce the memory demand of computer system and speed up CPU processing. And it is an important technical factor to prevent the occurrence of overfitting [6].

17.2.3 Pooling

The main function of pooling operation in the whole convolutional neural network is to keep the model graphics consistent in translation, rotation, scaling, and perspective. In practical applications, pooling is divided into types such as maximum pooling and mean pooling. Among them, the mainstream application method maximum pooling refers to the maximum value of the output pooling area, and the average pooling refers to the average value of the output pooling area.

17.3 Application of Convolutional Neural Network in Image Processing

17.3.1 Image Identification

Image recognition mainly includes three links, namely data preprocessing, feature extraction, and discriminant classification. Data preprocessing is to save the key information in the image and to facilitate the subsequent feature extraction operation. In data preprocessing, there are methods such as image normalization and median filtering. Feature extraction is an abstraction of the original image. The simplified convolutional neural network structure as an extractor can identify the extracted features to the image during the discriminant classification stage. Among them, the methods used in discriminating classification are mainly hidden Markov models, support vector machines based on kernel functions, artificial neural networks, and so on.

17.3.2 Image Semantic Segmentation

Image semantic points can get more information on the collection and analysis of feature sets. It is widely used in medical, criminal investigation, and other fields such as organs or lesions in MR images, cell structures or tumor areas in pathological images. Although the benchmark data has achieved good results, the depth segmentation model has poor generalization ability to unknown datasets due to partial data transfer. This regional migration is more common in histopathological image analysis [8].

The algorithm mainly attempts to align the visual appearance or characteristic distribution between the source domain and the target domain. We propose an adaptive algorithm in the field of histopathology image segmentation, namely the double adaptive pyramid network (DAPNet). The proposed DAPNet reduces the difference between the two domains by combining two domain adaptive components at the image and feature levels. Image-level adaptation considers the overall difference between the source domain and the target domain, such as the color and style of the image, while feature-level adaptation considers the spatial inconsistency between the source domain and the target domain. Specifically, some strategies are used to learn. Firstly, we developed a deep unsupervised domain adaptive algorithm for image segmentation of histopathology. Secondly, we propose two regional adaptive components based on pyramid features to mitigate regional differences in image and feature levels, which provide smarter and more accurate detection methods for modern medical [9]. As shown in Fig. 17.1, both the source image and the target

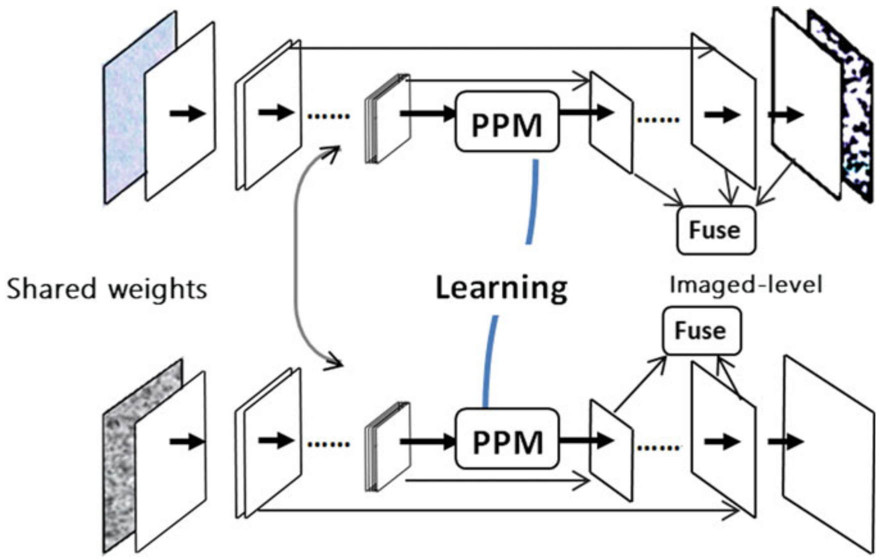

Fig. 17.1 Output image label close to the source domain

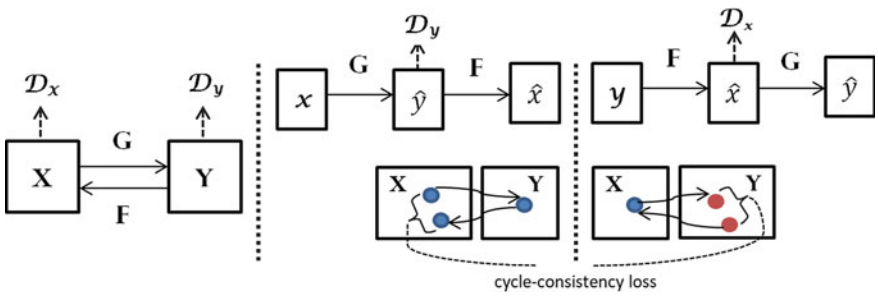

Fig. 17.2 Dx and Dy refer to the discriminator

image are input to the segmentation network, to make it easier to output some images and labels.

17.3.3 Object Detection

The latest methods apply the same idea to conditional image generation applications. The key to the successful application of this image processing technique is that the generated image is in principle indistinguishable from the real one. This leads to a particularly large task of image generation, and this is precisely the goal of many computer graphics optimization. The anti-loss method is used to learn the mapping, which makes the transformed image indistinguishable from the image in the target domain. Using a single input to train a non-parametric texture model on an image pair, the concept of object matching between images dates back at least to earlier image analogies. It is very effective to use the convolutional neural network to learn the parameterized translation function [10]. The method is based on the "pix*pix" framework, which uses a conditional inverse transformation network to learn the mapping from input to output image. Similar functions have been applied to different tasks, such as generating photos from sketches, or generating photos from attributes and semantic layout [11]. Compared with other image processing techniques, the biggest difference of this kind of learning mapping is that there is no paired training example. As shown in Fig. 17.2, the object detection involves matching between the target domain and the source domain and Dx and Dy refer to the discriminator.

17.4 The Conclusion

Deep learning based on convolutional neural networks is a situation where today's technology is developing faster and faster. As a method of information processing by computer technology simulating human brain thinking, it has important meaning in the application of artificial intelligence. In deep learning, neural networks have a greater advantage in image processing than traditional image processing methods. They can extract more and more complex features of images. They have applications in various industries in society and have changed people's lifestyles. In this paper, the relevant concepts of image processing technology for electronic information based on convolutional neural network are expounded, and the application of convolutional neural network in image processing is briefly introduced based on the current development of technology, which is expected to be helpful for scholars in related fields to study related problems.

Acknowledgements This paper is funded by Project of:

1. Scientific Research Fund of Hunan Provincial Education Department, Research on Intelligent Medical Logistics Distribution based on Particle swarm optimization (No. 19C1708).

2. Chenzhou Municipal Science and Technology Project, Research on key technologies of intelligent parking in smart city (No. zdyf201913).

3. Chenzhou Municipal Science and Technology Project, Research on AR system based on Chenzhou Mining Fair (No. zdyf201911)

4. Hunan Provincial Department of Education Fund, Computer Application Technology Innovation and Entrepreneurship Education Center, (No. [2018] 380)

5. Hunan Provincial Department of Education Fund, Big Data and Processing Innovation Entrepreneurship Education Base (No. [2019] 333).

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