Scholar Publishing Group
International Journal of Neural Network
https://doi.org/10.38007/NN.2022.030206
ISSN 2790-2692 Vol. 3, Issue 2: 44-51

Deep Learning in Digital Medical Image Recognition

Huikai Wang[1*], Yiming Jiang[2] and Hua Zhuang[1]

[1]*Binzhou Hospital of Traditional Chinese Medicine (Binzhou Medical University TCM Hospital), Shandong, China*

[2]*Yantai Affiliated Hospital of Binzhou Medical University, Shandong, China*

bytcmwhk@bzmc.edu.cn

[*]*corresponding author*

Keywords: Deep Learning, BP Neural Network, Digital Medicine, Image Recognition

Abstract: The development of digital medical imaging occupies a large proportion in modern medical care. With the continuous development of computer technology, intelligent medicine is inseparable from the identification of digital medical image information, which is playing an important role in clinical diagnosis and scientific research. In order to solve the shortcomings of existing digital medical image recognition research, based on the discussion of Gabor digital medical image functional equation and deep learning image semantic segmentation, this paper aims at the sample data and parameter settings of deep learning digital medical image recognition application. A brief introduction was given. And the design and discussion of the digital medical image recognition model structure of deep learning BP neural network, and finally the sensitivity (SE), specificity (SP), accuracy of the recognition results of the deep learning BP neural network digital medical image recognition model designed in this paper. The rate (AR) is experimentally compared with the (SVN) and (RNN) models. The experimental data show that the sensitivity (SE) and specificity (SP) of the deep learning BP neural network are compared with the (SVN) and (RNN) models. , the accuracy rate (AR) is higher, reaching an average of 0.91. It is significantly higher than the (SVN) and (RNN) models, so it is verified that the model designed in this paper has better classification effect, perception ability and discrimination ability in digital medical image recognition.

1. Introduction

With the vigorous development of Internet big data and computer technology, the boom of deep learning has already swept across all walks of life. In academia and medicine, deep learning methods have already played an important role in intelligent technology fields such as image processing and recognition.

Nowadays, more and more scholars pay attention to the research of various computer technologies and system tools in digital medical image recognition, and have achieved certain research results through practical research. Valkonen M proposed a multi-level medical image fusion to fuse medical image information of different levels into a unified output, which is conducive to more efficient and scientific medical image processing such as non-invasive diagnosis and image-guided surgery. The main purpose of Valkonen M's research is to model the fusion of medical images as a pattern recognition task. Classify the original image by quaternary transformation. Subsequently, features are extracted from medical images using different activity metrics. These features are then image-fused through image splitting and classifiers. Finally, the proposed method is compared with three fusion methods, and the reliability and effectiveness of the method in application are verified [1]. The application of Patel S M artificial intelligence in medical imaging is of particular value, in cardiology focused on automated image recognition, for which Patel S M describes a digital medical imaging system for synthesizing medically enhanced digital images. Patel SM introduced the structure, theoretical basis and specific application of the method, applied to the situation of intravascular digital images. Convolutional Neural Network Model Generation for Recognition of Intravascular Ultrasound Images Using Training Conditions on Digital Images of Angiosclerosis. With this simple recognition model, useful information for images can be quickly generated. Medical imaging quality can be achieved through this technology [2]. Kavya E developed a deep learning-based medical imaging recognition for automated epithelial cell image detection. Partially pretrained deep convolutional neural networks were fine-tuned using batches of images from 123 patient samples of invasive breast tumors. The effectiveness of deep learning-based digital epithelial cell imaging recognition was verified by comparing epithelial cell imaging with cytokeratin images and performing visual assessment of medical images. After applying deep learning-based epithelial cell imaging recognition, it was concluded that In conclusion, deep learning can be used to detect cancer cells in breast cancer imaging stained with conventional brightfield IHC [3]. Although the existing research on digital medical image recognition is very rich, the research on digital medical image recognition based on deep learning BP neural network still has certain limitations.

Therefore, in order to enrich the existing research on digital medical image recognition, this paper firstly introduces the functional equation of Gabor digital medical image and the concept of deep learning image semantic segmentation, and then discusses the digital medical image recognition model of deep learning BP neural network designed in this paper. The applied parameter settings and sample data, and finally the digital medical image recognition model architecture of the deep learning BP neural network is designed, and the experimental test is carried out through the effect of the designed model on CT lung images. Application effectiveness of deep learning BP neural network digital medical image recognition model.

2. Deep Learning for Digital Medical Image Recognition

2.1. Deep Learning

(1) Fully convolutional network

Image semantic segmentation not only requires the machine to segment the contour of the target domain in the image, but also accurately identify the semantic category to which the target region belongs [4]. To be precise, semantic segmentation is pixel-level image classification, which requires intensive prediction of images [5].

1) Deep learning is only applied to semantic segmentation as a classifier, that is, the image blocks of fixed size are selected by sliding in turn, and the image blocks are sent to the

convolutional neural network classifier to classify the target pixels in the image block [6]].

2) In the fully convolutional network, the pooling layer can integrate the spatial dimension information while increasing the receptive field, making the classification of pixels more accurate [7]. If the interpolation method is simply used for upsampling, the obtained segmentation result is bound to be rough [8].

(1) Feature fusion

After the fully convolutional network is proposed, the main work focuses on how to effectively integrate the category information of digital medical images, so as to improve the performance of digital medical image segmentation models [9]. There are three main ideas: atrous convolution, pyramid pooling, encoding and decoding structure [10].

1) Atrous convolution

Although the pooling operation in the convolutional network can improve the size of the receptive field of the predicted pixels of digital medical images, it reduces the resolution of digital medical images and loses necessary location information [11]. Dilated convolution or dilated convolution is equivalent to adding zero padding to the original convolution kernel. Using dilated convolution can increase the size of the receptive field exponentially without changing the resolution of digital medical images [12] .

2) Pyramid Pooling

The pooling method to form digital medical images of different scales can also help the model to obtain multi-scale information. If the digital medical images are stacked, a pyramid-like structure is formed, and the pyramid can realize real-time segmentation of high-resolution digital medical images by cascading feature fusion units.

3) Encoding and decoding structure

The main idea of this structure is to use shallow features to supplement the lost details of high-level digital medical image prediction. The encoding-decoding structure often contains a series of skip connections and is widely used in the field of digital medical image segmentation [13].

2.2. Gabor Digital Medical Imaging

The Gabor function is a linear filter that can be applied to digital medical image edge extraction, and is suitable for digital medical image texture characterization and differentiation [14]. Gabor filtering can well characterize the feature information of digital medical images in spatial scale and direction [15]. Therefore, digital medical image features enhanced by Gabor filter can improve digital medical image texture features [16]. The CT lung image filtered by the Gabor function can be expressed as:

$$H_{\lambda,\gamma}(u,v) = K(u,v) * \varphi_{\lambda,\gamma} = \int_{t=-\infty}^{+\infty}\int_{s=-\infty}^{+\infty} K(u,v)\varphi_{\lambda,\gamma}(t, v-s) \tag{1}$$

Where $K(u,v)$ represents the input CT lung image, $\varphi_{\lambda,\ \gamma}(u,v)$ represents the classification response when the Gabor filter pixel is λ and the resolution is γ, and the $*$ symbol in formula (1) represents the neural network convolution recognition, and the mathematical expression can be defined as :

$$\varphi(u,v) = \exp\left(\frac{u^2+\theta^2 v^2}{2\alpha^2}\right)\exp\left(k\left(2\pi\frac{u^2}{\vartheta}+\psi\right)\right) \tag{2}$$

$$\begin{cases} u^{'} = u\cos\eta + v\cos\eta \\ v^{'} = -u\cos\eta + v\cos\eta \end{cases} \tag{3}$$

In Equation (2), u and v represent the pixels of the image, and ϑ represents the image wavelength [17]. η represents the direction of the filter; ψ represents the phase shift of the activation function of the BP neural network; θ represents the aspect ratio of the Gabor function. α stands for the standard deviation of the Gabor function. Through Gabor filtering, the same pixels in CT lung images will have multiple feature expressions, so as to obtain various image texture features [18].

3. Research on the Application of Deep Learning in Digital Medical Image Recognition

3.1. Application Parameter Setting of Deep Learning in Digital Medical Image Recognition

Model parameters are an important part of neural network in the training of digital medical image recognition, which can directly affect the learning speed and final learning effect of neural network. When using the backpropagation algorithm to train model weights, how to set the parameters often determines the success of the final model training. In the convolutional neural network, the main parameters include: loss function, activation function, learning rate, optimizer, number of iterations, etc. The specific model parameters are shown in Table 1:

Table 1. Model parameters

Parameter item	Parameter information	Parameter value
Loss function	Binary cross entropy	Binary categorical cross entropy
Weight factor	Coefficient initialization	Inh.5
Learning rate	Rate initialization	0.02
Optimization project	Optimizer	Adam
Iterate	Frequency	2000
Activation function	Activation function	Sigmoid

3.2. Application Sample Data of Deep Learning in Digital Medical Image Recognition

In the CT lung image data set in this paper, a total of 20 cases of CT lung images were collected, a total of 200 CT lung images, and a total of 100 of them met the criteria for clinical diagnosis after screening. According to the human visual standard of CT lung image, the specific processing method of the original CT image in the MRI data set of this paper is: set the thresholds -2000 and +500. Set the pixel value greater than +500 in the image to 1, and set the pixel value less than -2000 to 0 to obtain a black and white image with a resolution of 512x512. The original CT lung image is not suitable for direct processing by the machine, and needs to be pre-processed. deal with. Table 2 shows the HU value corresponding to each tissue in the human body (the HU value can measure the radiation dose). According to the corresponding HU value of the human tissue, the DICOM file can be processed to retain and highlight the tissue details suitable for lung cancer identification.

Table 2. HU values corresponding to each tissue of the human body

Part name	HU
Air	-2000
Water	0
Cerebrospinal fluid	20
Kidney	35
Blood	+35 to +45
Muscle	+20 to +50
Liver	+45 to +65
Skeleton	+800 and above

4. Application Research of Deep Learning in Digital Medical Image Recognition

4.1. Construction of Deep Learning Digital Medical Image Recognition System

The deep learning BP neural network classification method is a supervised classification method. In this paper, the EI digital medical image processing software will be used to perform unsupervised identification of digital medical images, thereby generating initial classified images. Then, according to this image, the corresponding type of training samples are obtained, and then the deep learning BP neural network classifier is used for secondary classification. The specific system structure is shown in Figure 1:

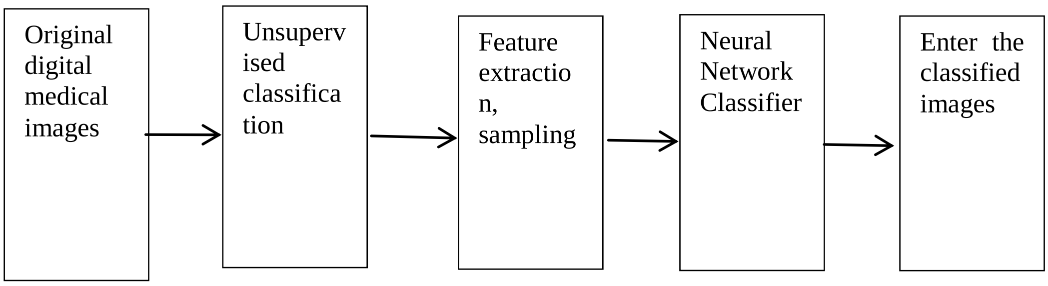

Figure 2. Structure diagram of deep learning digital medical image recognition system

The specific steps of the digital medical image recognition system based on the combination of EI digital medical image processing software and deep learning BP neural network are as follows:

(1) First, with the aid of EI digital medical image processing software, the BP neural network model is used to conduct unsupervised analysis of digital medical images. Compare the initial digital medical image with the initial classified digital medical image to determine the final pre-classified digital medical image number.

(2) Second, obtain training data and test data on the original digital medical images, and train the BP neural network classifier through the input. Perform digital medical image classification training on samples of a known class of digital medical images,

(3) Finally, input the trained BP neural network classifier to obtain the information of digital medical image recognition.

4.2. Application of Deep Learning in Digital Medical CT Lung Image Recognition

In order to verify the performance effect of the deep learning BP neural network (DL-CNN) proposed in this paper in CT lung image recognition, this paper uses the sensitivity (SE), specificity (SP), and accuracy (AR) as the CT lung image recognition. The evaluation index of image recognition performance effect. Among them, the higher the accuracy rate (AR), the better the classification effect of the model for CT lung images; the higher the sensitivity, the stronger the perception ability of the model for CT lung images; the higher the specificity, the better the model for lung images. The normal discrimination ability is stronger. In order to reflect the superiority of the deep learning BP neural network model in this paper, the above indicators are calculated by ten-fold cross-validation, and the CNN and SVN models are used for testing and comparison in the CT lung image data collected in this paper. The performance test results are shown in Table 3:

Table 3. Performance test results

Model	DL-CNN	CNN	SVN
Sensitivity	0.897	0.714	0.685
Specificity	0.915	0.686	0.701
Accuracy	0.927	0.736	0.802

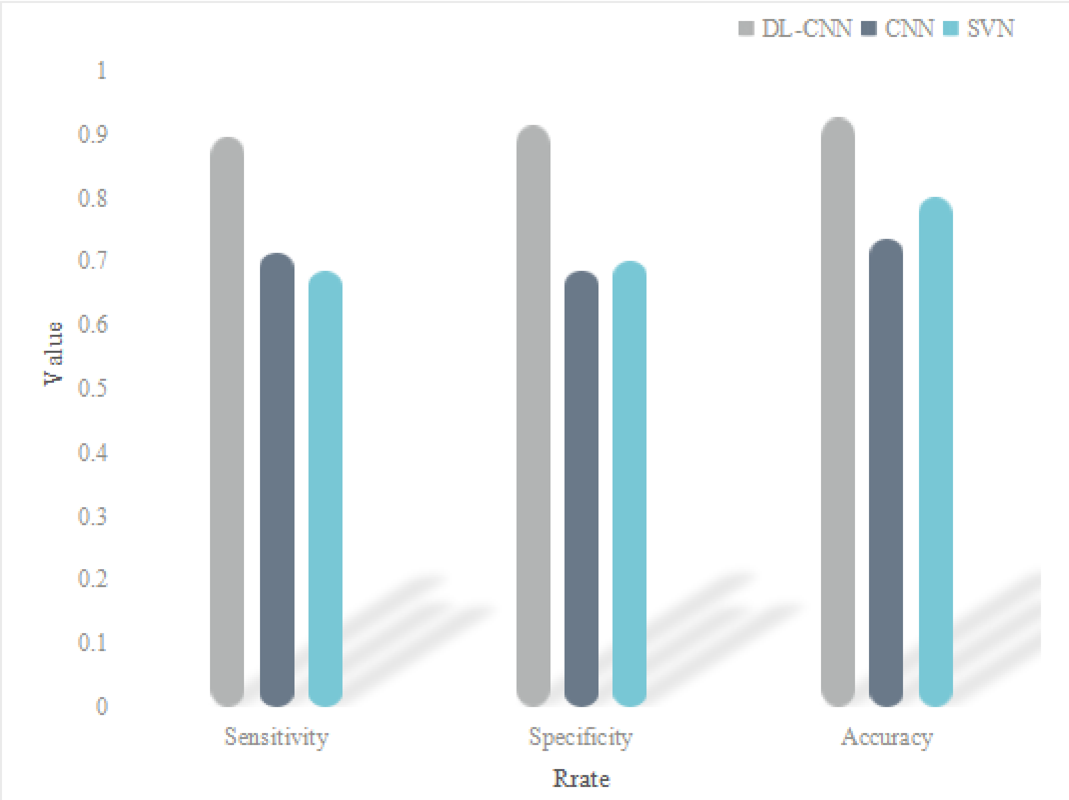

Figure 2. Comparison of performance test results

As can be seen from Figure 2, first of all, the sensitivity score of the deep learning BP neural network model is 0.897, respectively, which is better than that of the CNN and SVN models, indicating the perception ability of the deep learning BP neural network model proposed in this paper in CT lung image recognition. stronger. Secondly, the specificity score of the deep learning BP neural network model is also higher than that of CNN and SVN, with the highest score reaching 0.915, which proves that the deep learning BP neural network model has a stronger ability to discriminate normal CT lung images. Finally, the accuracy score of the deep learning BP neural network model is also higher than that of CNN and SVN, with the highest score reaching 0.897, indicating that the deep learning BP neural network model has a better effect on CT lung image classification.

5. Conclusion

This paper specifically expounds the technical basis of deep learning digital medical image recognition, including the functional equation of Gabor digital medical image and the description of deep learning image semantic segmentation, as well as the parameter settings and samples of deep learning BP neural network for digital medical image recognition. At the same time, it focuses on the design of the digital medical image recognition process framework of deep learning BP neural network. The experimental results of deep learning BP neural network in CT lung image recognition were compared with (SVN) and (RNN) models, which proved the superiority of the digital medical image recognition model using deep learning BP neural network.

Funding

This article is not supported by any foundation.

Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

References

[1] Valkonen M, Isola J, Ylinen O, et al. Cytokeratin-Supervised Deep Learning for Automatic Recognition of Epithelial Cells in Breast Cancers Stained for ER, PR, and Ki-67. IEEE Transactions on Medical Imaging, 2020, 39(2):534-542. https://doi.org/10.1109/TMI.2019.2933656

[2] Patel S M, Dharwa J N. Medical Image Enhancement through Deep Learning Methods. National Journal of System and Information Technology, 2018, 11(1):35-44.

[3] Kavya E. Performance Analysis of Different Filters for Digital Image Processing. Turkish Journal of Computer and Mathematics Education (TURCOMAT), 2021, 12(2):2572-2576.ER PR https://doi.org/10.17762/turcomat.v12i2.2220

[4] auro G, Ciprandi G, Deperte F, et al. Nasal cytology with deep learning techniques. International Journal of Medical Informatics, 2019, 122(FEB.):13-19. https://doi.org/10.1016/j.ijmedinf.2018.11.010

[5] Abdallah Y. Characterization of Cardiac Tissues using K-means Analysis Methods in Nuclear Medicine Images. Dokkyo Journal of Medical Sciences, 2021, 48(1):55-59.

[6] Kale V G, Malode V B. A Novel Approach based on Average Information Parameters for Investigation and Diagnosis of Lung Cancer using ANN. Pattern Recognition & Image Analysis, 2018, 28(2):301-309. https://doi.org/10.1134/S1054661818020098

[7] Kamath R, Balachandra M, Prabhu S. Crop and weed discrimination using Laws' texture masks. International Journal of Agricultural and Biological Engineering, 2020, 13(1):191-197. https://doi.org/10.25165/j.ijabe.20201301.4920

[8] *Hamed M, Massen R, Hendy H E. Imaging Approach for the Determination of Surfaces in Three-Dimensional Coordinates. International Journal of Applied Mathematics and Computer Science, 2018, 5(5):132-146.*

[9] *Vishwakarma A, Khare A. Moving Object Tracking System Using Morphological Image Processing. International Journal of Computer Sciences and Engineering, 2018, 6(7):88-93. https://doi.org/10.26438/ijcse/v6i7.8893*

[10] *Oluwasammi A, Aftab M U, Qin Z, et al. Features to Text: A Comprehensive Survey of Deep Learning on Semantic Segmentation and Image Captioning. Complexity, 2021, 2021(8):1-19. https://doi.org/10.1155/2021/5538927*

[11] *Abbas A, Abdelsamea M M, Gaber M M. DeTraC: Transfer Learning of Class Decomposed Medical Images in Convolutional Neural Networks. IEEE Access, 2020, PP(99):1-1. https://doi.org/10.1109/ACCESS.2020.2989273*

[12] *Kermany D S, Goldbaum M, Cai W, et al. Identifying Medical Diagnoses and Treatable Diseases by Image-Based Deep Learning. Cell, 2018, 172(5):1122-1131.e9. https://doi.org/10.1016/j.cell.2018.02.010*

[13] *Haenssle H A, Fink C, Schneiderbauer R, et al. Man against machine: diagnostic performance of a deep learning convolutional neural network for dermoscopic melanoma recognition in comparison to 58 dermatologists. Annals of Oncology, 2018, 29(8):1836-1842. https://doi.org/10.1093/annonc/mdy520*

[14] *N Sünderhauf, Brock O, Scheirer W, et al. The Limits and Potentials of Deep Learning for Robotics. The International journal of robotics research, 2018, 37(4-5):405-420. https://doi.org/10.1177/0278364918770733*

[15] *Araya-Polo M, Jennings J, Adler A, et al. Deep-learning tomography. Leading Edge, 2018, 37(1):58-66. https://doi.org/10.1190/tle37010058.1*

[16] *Grassmann F, Mengelkamp J, Brandl C, et al. A Deep Learning Algorithm for Prediction of Age-Related Eye Disease Study Severity Scale for Age-Related Macular Degeneration from Color Fundus Photography. Ophthalmology, 2018, 125(9):1410-1420. https://doi.org/10.1016/j.ophtha.2018.02.037*

[17] *Kemker R, Salvaggio C, Kanan C. Algorithms for semantic segmentation of multispectral remote sensing imagery using deep learning. ISPRS Journal of Photogrammetry and Remote Sensing, 2018, 145(NOV.):60-77. https://doi.org/10.1016/j.isprsjprs.2018.04.014*

[18] *Ranjan R, Sankaranarayanan S, Bansal A, et al. Deep Learning for Understanding Faces: Machines May Be Just as Good, or Better, than Humans. IEEE Signal Processing Magazine, 2018, 35(1):66-83. https://doi.org/10.1109/MSP.2017.2764116*