Research on Classification Algorithm of Liver Multi-Feature Fusion Based on Deep Learning

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Abstract: Hepatocellular carcinoma (HCC) is the third most common cancer in the world, which seriously threatens people's life and health. With the rapid development of medical imaging technology, it is of great significance to classify the benign and malignant tumors of HCC through computer-aided techniques. In this paper, a classification algorithm using the multiple deep features fusion is designed. By designing the feature fusion layer network based on the deep learning framework, the deep features and textural features are integrated; the end-to-end classification algorithm using deep learning feature fusion is realized, which has higher classification accuracy and algorithm stability, and can get better classification results than the traditional textural features.

1. Introduction

Hepatocellular carcinoma (HCC) is a common kind of malignant tumor. Its morbidity and mortality are in the forefront of all kinds of tumor diseases. China is also a high incidence area of the primary liver cancer. With the development of medical imaging technology, the noninvasive medical imaging plays a key role in the early detection, staging, treatment planning and response monitoring of liver cancer. However, in medical images, the boundaries of liver cancers are blurred; different doctors delineate tumors significantly differently. Based on the deep learning framework, a multiple feature fusion classification algorithm is designed in this paper. From the input of medical image to the output of classification results, a complete algorithm system is adopted to avoid connecting problems between different methods. It improves the classification performance of the whole algorithm. The classification results are superior to the traditional textural features; the accuracy of classifying benign from malignant liver tumors is also improved. The design provides reference to the clinical diagnosis of diseases.

2. Features of the Magnetic Resonance Images of Hcc

In recent years, liver magnetic resonance images (MRI) technology has made great progress. But the detection and recognition of chronic liver diseases, such as liver cancer, are still long-standing problems. There are usually three phases of MRI images in the enhancement scan: the arterial phase, the portal phase and the delayed phase. The image of each phase has a certain scanning duration. In a scanning cycle, the MRI equipment constantly intercepts image information, which constitutes the sequence image of each phase.

The MR images are obtained by scanning after the intravenous injection of contrast agents. After injecting the agents into the vein, they can flow to various tissues of human body with the blood. Due to the different blood supply and blood flowing speed of various tissues, the distribution and duration of contrast agents are also different, so the clearer MR images can be obtained. This MR technology can better detect liver lesions and determine the character. The method is superior to general scanning.

In this study, the delayed phase is also used in the classification of benign and malignant tumors. As an important phase of MR enhanced scanning, the delayed phase can also represent tumor information. The reasonable use of information of the delayed phase image can significantly

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improve the accuracy of HCC detection. At the same time, based on deep learning, this paper extracts the features of MRI images in the three phases, carries out the feature fusion, and comprehensively analyzes the feature information of tumor images in three phases. It provides a very powerful assistant for the accurate diagnosis of HCC.

3. Image Fusion Technology

The purpose of image fusion is to extract the useful information of each channel through image processing and computer techniques based on the collected multichannel information, and then carry out the comprehensive processing, so as to effectively improve the utilization rate of image information, enhance the accuracy of images and improve the accuracy of information. The traditional image fusion algorithm can be divided into three levels according to the level of fusion processing: data fusion, feature fusion and decision fusion.

Data fusion means to directly fuse the original data information before the feature layer processing. This fusion method has the highest accuracy. Compared with other image fusion methods, data level image fusion can get more accurate image information. At the same time, the fusion images obtained through multi-source image data can absorb and play the advantages of different imaging technologies and different data sources. The data fusion is less difficult than image fusion. It is also the most widely used image fusion method in current research. However, the disadvantages of data-level image fusion are also obvious. It operates according to image pixels, so during the image preprocessing, the amount of information is very large, which puts very high requirements for the computer performance. If there are too many multi-source images, the processing time of image fusion will increase dramatically. Therefore, the advantages and disadvantages of data fusion are very obvious. The method is more often used for the analysis and understanding of images in daily application.

The feature fusion belongs to the middle level image fusion, which can get the fused image features and prepare for the later classification decision. The feature fusion method compresses image information. Compared with the pixel fusion, its processing speed is faster. It also consumes less memory and time. At the same time, it extracts image features as fusion information, and makes full use of the useful information of images. It is the most common image fusion processing method. At the same time, different feature extraction methods will bring different feature information to the image. The key to feature fusion is to deeply dig image features and make full use of relevant information as well as difference information between features.

Decision fusion is a top-level image fusion method; its abstract level is the highest. It uses different classifiers to analyze and make decisions on the same object's feature information, and then make fusion decisions on all decision information according to a certain fusion strategy. The final decision result will be the optimal decision for the overall situation.

4. Research on the Image Fusion Technology Based on Deep Learning

As a new artificial intelligence method, deep learning can not only extract image features, but also realize image classification in the field of image processing. It changes the modular design of previous image processing algorithms, so that the whole image classification algorithm can realize the end-to-end model. Therefore, image fusion methods based on deep learning mainly focus on feature fusion and decision fusion.

The convolution neural network is the most important method of deep learning in the field of image. It is a muti-layer neural network structure. A typical convolution neural network is composed of the convolution layer, the pool layer and the full connection layer. Among them, the convolution layer and the pooling layer are combined to extract image features layer by layer, and output to the classifier through several full connection layers to complete image classification. A convolutional neural network structure is recorded as a channel in the muti-feature fusion method of deep learning. The multiple deep features fusion algorithm usually has multiple inputs and multiple convolutional neural network channels. Finally, through a certain fusion strategy, the features of multiple channels are comprehensively used to get the final classification result.

A typical convolutional neural network is generally composed of the input layer (Input), the convolution layer (Conv), the pool layer (Pool), the full connection layer (FC) and output layer (Output).

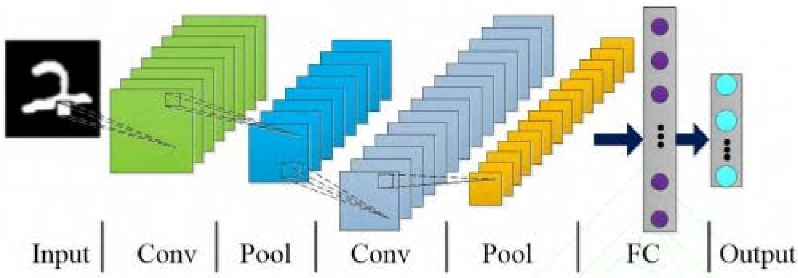

Fig.1 Typical Structure of the Convolutional Neural Network.

In order to extract different features of the input data, multiple convolution kernels are often used to convolute the input image and obtain several feature images. The process of generating convolution layers can be described as follows.

$$x_j^l = f\left(\sum_{i \in M_j} x_i^{l-1} * W_{ij}^l + b_j^l\right) \tag{1}$$

In the formula, x_j^l and x_i^{l-1} respectively represent the output of the channel j of the convolution layer l and the output feature diagram of the previous layer; W_{ij}^l is the convolution kernel which connects the i feature diagram of the convolution layer l and the j feature diagram of the $l-1$ layer. b_j^l is the offset of the j feature diagram of the layer l; M_j represents the subset of any currently input feature diagram. * represents the convolution operation; f represents the activation function.

The convolution layer is usually followed by the pool layer. According to certain down sampling rules, the feature diagrams are down sampled to reduce the dimensions of feature diagrams and maintain the scale invariance of features. After the alternate transferring of multiple convolution layers and pool layers, features for the image identification are output through the full connection layer.

There are two methods of fusion strategy design. The first is feature fusion, which combines multiple deep features of the image in series through multiple full connection layers to form a long feature vector, and then outputs it to the Softmax classifier for classification. The final classification results can be obtained. This feature fusion method is simple to implement and easy to calculate. But if there are too many combined features, the high feature dimension will increase the hardware computing load. Too many feature dimensions will also lead to redundant features, which will affect the final classification. Therefore, this fusion method needs to be combined with additional feature selection or feature dimensionality reduction technologies to keep the stability of classification results.

5. Process Design for the Muti-Feature Fusion Classification Algorithm Based on Deep Learning

Based on the characteristics of muti-phase MRI and the advantages of end-to-end muti-feature fusion deep learning framework, an end-to-end multiple deep features fusion classification algorithm is designed. The algorithm consists of two parts: the image preprocessing and the end-to-end muti-feature fusion classification model based on deep learning.

In the image preprocessing part, images of the three phases of MR scanning are selected from the liver cell carcinoma MR images collected by the hospital: the arterial phase, the portal phase and the unenhanced scanning phase. Afterwards, the three-dimensional re-sampling is carried out for images of each phase according to the ROI region of the tumor to obtain the re-sampling data of the axial view, the coronal view and the sagittal view. Finally, the data sets for deep learning multi-feature fusion classification training can be obtained.

The end-to-end multi-feature fusion classification model based on deep features is divided into two stages: the training stage and the testing stage. In the training stage, the data image of each view and each mode is loaded into the convolutional neural network model to obtain the deep features of training. Then, using the neural mechanism of the full connection layer in the convolutional neural network, a cascaded feature fusion method is designed. Firstly, the three view features of different phases are fused, and then the fusion features of the three phases are further cascaded fused. That is the processing of two-level cascade fusion. Afterwards, the final fusion features are obtained and finally connected to the Softmax classifier to get the final classification results. The parameter weights of the whole training network are gradually optimized and improved. The whole training process is carried out on the Caffe deep learning platform. After the training, the trained convolutional neural network is saved for the use in the testing stage. In the testing stage, the final test classification results can be obtained by loading the multiple view data for test into the trained convolutional neural network training model.

6. Conclusion

This paper mainly studies the design of multi-feature fusion classification algorithm based on the deep learning framework. Firstly, a cascaded fusion layer network under the deep learning framework is designed for the fusion of deep features of multiple phases and multiple views of HCC tumors. Then, an experiment of multi-feature fusion classification algorithm based on deep learning is designed, and the experimental data set is established. In the Caffe deep learning framework, the multi-feature fusion classification algorithm is implemented. In the multi-feature fusion method. At present, the feature fusion method of deep learning still focuses on series joining, ignoring the relevance and difference of various features before. The convolutional neural network and the fusion layer designed in this paper can not only effectively fuse the information of multiple features, but also achieve the end-to-end fusion and classification of multiple deep features. The whole image classification process is designed to improve the classification accuracy of the end-to-end model.

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References

[1] Guan, C.T., Zhao, H., Li, X.Q., et al. (2017). Basic Characteristics and Survival Analysis of Patients with HCC. Chinese Journal of Oncology, vol. 39, no. 3, pp. 231-235.

[2] Wang, C., Elazab, A., Wu, J., et al. (2016). Lung Nodule Classification Using Deep Feature Fusion in Chest Radiography. Computerized Medical Imaging & Graphics, no. 57, pp. 10-18.

[3] Liu, J., Jiang, Y., Li, Z., et al. (2015). Partially Shared Latent Factor Learning With Multiview Data. IEEE Transactions on Neural Networks & Learning Systems, vol. 26, no. 6, pp. 1233-1246.

[4] Shin, H.C., Roth, H.R., Gao, M., et al. (2016). Deep Convolutional Neural Networks for Computer-Aided Detection: CNN Architectures, Dataset Characteristics and Transfer Learning. IEEE Transactions on Medical Imaging, vol. 35, no. 5, pp. 1285-1298.

[5] Albarqouni, S., Baur, C., Achilles, F., et al. (2016). Agg Net: Deep Learning From Crowds for Mitosis Detection in Breast Cancer Histology Images. IEEE Transactions on Medical Imaging, vol. 35, no. 5, pp. 1313-1321.