Application and Research of Convolution Neural Network in MRI Image Classification and Recognition

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Abstract. The traditional hepaticcell carcinoma (HCC) pathological grading depends on biopsy, which will cause damage to the patient's body and is not suitable for everyone's pathological grading diagnosis. The purpose of this paper is to study the pathological grading of liver tumors on MRI images by using deep learning algorithm, so as to further improve the accuracy of HCC pathological grading. An improved network model based on SE-DenseNet is proposed. The nonlinear mapping relationship between feature channels is modeled and recalibrated using attention mechanism, and rich deep-seated features are extracted, so as to improve the feature expression ability of the network. The method proposed in this paper is verified on the data set including 197 patients, including 130 training sets and 67 test sets. The experimental results are evaluated by receiver operating characteristic (ROC) and area under the ROC curve (AUC). The improved SE-Densenet network achieves good results, and AUC 0.802 is obtained on the test set. The experimental results show that the method proposed in this paper can well predict the pathological grade of HCC.

1. Introduction
Early diagnosis of liver tumor is of great significance to the formulation of treatment plans. For advanced tumor, it is necessary to clarify the heterogeneity information of tumor such as molecular biology classification and grading before treatment, and to select a reasonable treatment plan according to the heterogeneity of tumor. Clinical practice has shown that the pathological grading information of tumor is closely related to the curative effect and prognosis of patients, but the pathological grading method relying on puncture biopsy and surgical pathological sampling is not suitable for pre-treatment diagnosis of all tumor. Magnetic Resonance Imaging (MRI) is a common imaging diagnostic method, but the naked eye still has limitations in the diagnosis of early liver tumor, and the value of heterogeneity assessment of tumor has not been fully excavated.

Pathological grading of liver tumor based on medical images is now mostly based on traditional methods. For example, Ganeshan[1] performed texture analysis on non-enhanced CT images of 21 cases of esophageal cancer to find out the relationship between image features, tumour grade and survival. Mu[2] made clinical staging diagnosis of 42 cervical cancer patients by extracting the textural characteristics of the images. Guo[3] analyzed breast dynamic enhanced magnetic resonance imaging and gene data collected from 91 patients to study the pathological grade of breast cancer. Wu and Gao[4] studied the pathological classification of HCC on T1 weighted image (T1WI) and T2
weighted image (T2WI) by using radiomics method, extracted high-dimensional radiomics features, established a prediction model by using machine learning method and achieved good research results.

The research of tumor pathological grading mainly uses the traditional machine learning methods in the above improved literature. Feature extraction is usually designed manually and then feature selection methods are used to select features that are highly correlated with the predicted categories. Traditional multiple linear regression and logistic regression methods are used to fit the linear mapping relationship between features and predicted values or categories. The feature types extracted by traditional machine learning methods mainly include low-level features such as tumor gray, texture, shape and size. These pixel-based features need more people's prior knowledge to design and extract them manually. It is a very time-consuming and laborious method, which will cause the instability of the results.

In recent years, convolutional neural network (CNN) has made great progress in image processing, such as image classification, image recognition, image segmentation and other fields. Many researchers have applied CNN to the task of medical image classification. CNN gradually surpasses human recognition ability in natural image classification tasks from 8 layers AlexNet [5] to 19 layers VGG [6], 22 layers GoogLeNet [7] and finally to 152 layers ResNet [8], and the number of network layers is increasing, network depth is increasing gradually, and network width is also improving. CNN pays more attention to the high-level semantic information represented by different categories of images. It can extract more and more abstract high-level semantic information from input images layer by layer directly, and update network model parameters according to target categories. Therefore, the convolution neural network can be used to extract high-level semantic features directly from liver tumor MRI images to obtain pathological grade. An improved network model based on DenseNet and SEnet (Squeeze-and-Excitation, SE) [9] is proposed in this paper, which can extract rich high-level semantic features, recalibrate the feature channels by using the attention mechanism, and model the relationship between the feature channels. This study mainly uses the convolution neural network algorithm based on SE-Densenet to study the pathological grading of HCC in MRI images.

2. Method

2.1. Review of DenseNet

DenseNet is proposed by Huang [10] in 2017, this model that each layer of the network should be connected with other layers of the network. It takes the characteristic map of all layers before the network as the input of the new layer, and the output of the layer as the input of the subsequent layers, as shown in Figure 1. If the network has L layer, DenseNet has L(L + 1) direct connections. The interconnection of network layers enhances the reuse of features, so that the final classifier makes decisions based on all the feature maps of the whole network.

![Figure 1. Structure of Dense Block](image)

In addition to the traditional convolution layer, pooling layer and classification layer, the main body of DenseNet includes several Dense Block modules and transformation layer. The Dense Block module contains multiple 1 × 1 and 3 × 3 convolution operations, and the convolution layers are connected in pairs. The output feature maps of the combined two convolution layers are operated by rectified linear unit (ReLU) operation and batch normalization (BN) operation to prevent gradient dispersion and maintain network nonlinearity. An important parameter of Dense Block is the growth
rate of the network, that is the number of convolution cores in each convolution layer, the number of output feature maps after each convolution operation. The transformation layer mainly includes 1 × 1 convolution layer, average pooling with stride = 2, BN operation and ReLU activation function.

2.2. Review of SENet
After a series of feature maps obtained by convolution pooling, in fact, the importance of each channel is different, each channel should have an important weight. Then the importance weight of each channel multiplied by the original value of each channel is the real feature map.

The basic idea of SE net is given below: using global average pooling to compress the whole channel into a channel descriptor:

\[ Z_c = F_{sq}(u_c) = \frac{1}{H \times W} \sum_{i=1}^{H} \sum_{j=1}^{W} u_c(i,j) \]  

(1)

\( Z_c \) represents a compressed vector, representing the C-th feature map, then to employ a simple gating mechanism with a sigmoid activation:

\[ s = F_{ex}(z, W) = \sigma(W_2 \delta(W_1 z)) \]  

(2)

\( \delta \) refers to the Relu activation function. \( W_1 \) and \( W_2 \) are the weights of the two fully connected layers for dimensionality reduction and dimensionality enhancement. Formula 1 limit the complexity of the model and formula 2 assist model generalization. The final output of the block is obtained by rescaling \( U \) with the activations \( s \):

\[ x_c = F_{scale}(u_c, s_c) = s_c u_c \]  

(3)

\( F_{scale}(u_c, s_c) \) refers to channel-wise multiplication between the scalar \( s_c \) and the feature map \( u_c \).

2.3. SE-DenseNet model
Our proposed model structure is shown in Figure 2. After DenseNet's output, a large number of feature maps are stacked together and sent to SE net module. Global average pooling followed by two FC (Fully connected layer) layers, the ReLU function is located in the middle of two FC layers, finally, it passes through sigmoid function. At the end of Dense Block, fine-grained features and self-adaptively adjusted depth features are combined by Concat operation. The number of layers of three densely connected blocks in the SE-DenseNet is 12, 16, 32, respectively.
3. Experiments and results

3.1. Data Set
The study was approved by the author's organization. We collected MRI image samples of 197 patients with HCC in Henan Provincial People's Hospital from 2012 to 2016. The training set includes 130 samples and the test set includes 57 samples. The inclusion criteria of experimental samples mainly include: patients have not been treated before, MRI examination before operation, clear image and complete HCC pathological analysis results.

The MRI images acquisition machine is MR750 (GE Healthcare), and the image resolution is 512 x 512. The collected original liver tumor image has high resolution and includes many images of non-tumor area, which will bring computational burden to the convolutional neural network and reduce the prediction ability of HCC pathological grade. Therefore, the original tumor image is processed, the image of tumor area is extracted and scaled to the resolution of 214 x 214. In order to increase the training samples, data augmentation operations are used on training dataset by rotating, flipping and scaling, in order to improve the performance of convolutional neural network.

The patient's HCC pathological grading report recorded the patient's detailed pathological grading results. Edmondson I, I-II and II grades belong to low-grade tumor, and Edmondson II-III, III, III-IV and IV belong to high-grade tumor. The purpose of this paper is to use convolution neural network algorithm to classify and identify high-low grade tumor. Figure 3 shows the HCC MRI example of high-low grade tumor.

3.2. Training Strategy
The equipment used in the experiment is NVIDIA GeForce GTX 1080 Ti. The network uses the cross entropy loss function and uses the end-to-end training mode for training. The BN parameters are trained with decay = 0.995. After training on the training set with 200K iterations and initial learning rate = 0.001, with using Adam optimizer, the training is finished. We apply data augmentation to improve the over-fitting problem of model.

3.3. Results and Discussion
The results of the experiment are shown in Table 1. Our method implements AUC 0.802 and achieves the best results among all the listed methods. Some traditional methods use manual extraction of low-level features, and use KNN, SVM, RF and other methods to construct classifiers. Obviously, the recognition rate is lower than that of CNN model. The results in Table 1 and Figure 4 show that the deep learning method is obviously better than the traditional machine learning methods. The performance of SE-DenseNet proposed in this paper is obviously better than that of traditional
methods. In terms of sensitivity, specificity, accuracy and AUC, the performance is improved by more than 10%.

From the Figure 4, the SE-DenseNet can distinguish high-grade and low-grade patients well. It shows that SE-DenseNet can obviously improve the classification performance after adding the SENet module compared with the original DenseNet. Compared with other CNN models, the performance of this method is improved by more than 4% - 8% in sensitivity, specificity, accuracy and AUC. The experimental results verify that the convolution neural network model proposed in this paper can mine and evaluate the heterogeneity of HCC. The next step of this study can focus on collecting more patient sample data and conducting multicenter cross validation studies.

![Figure 4. The ROC of classification results](image)

### Table 1. The results of HCC pathological grading

| Method     | Sensitivity | Specificity | Accuracy | AUC   |
|------------|-------------|-------------|----------|-------|
| KNN        | 64%         | 65%         | 64.44%   | 0.6651|
| RF         | 68%         | 65%         | 66.11%   | 0.6845|
| SVM        | 64%         | 69%         | 66.22%   | 0.6963|
| GoogleNet  | 69%         | 70%         | 69.31%   | 0.7049|
| ResNet51   | 70%         | 71%         | 70.38%   | 0.7289|
| DenseNet   | 74%         | 72%         | 73.46%   | 0.7526|
| SE-DenseNet| 77%         | 78%         | 79.75%   | 0.8021|

### 4. Conclusion

A novel method for pathological grading of HCC based on convolutional neural network is proposed. The DenseNet model is improved, and the attention mechanism is used to reposition the feature channel to improve the classification performance of the DenseNet model. Overall, a deep learning model SE-DenseNet was developed to predict high- versus low-grade HCC patients. The experimental results also show that CNN network can correlate the heterogeneity of HCC with images, and apply the results to the preoperative grading diagnosis of patients. As a non-invasive detection method, CNN network improves the accuracy of diagnosis and the determination of treatment plan.
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