Effective Combination of 3D-DenseNet's Artificial Intelligence Technology and Gallbladder Cancer Diagnosis Model

Xinyu Zhao [1,*], Bo Liu [2], Qunwei Lin[3], Jiaxin Huang [4], Liqiang Yu [5]

[1] Information Studies, Trine University, Phoenix, USA
[2] Software Engineering, Zhejiang University, Hangzhou China
[3] Information Studies, Trine University, Phoenix, USA
[4] Information Studies, Trine University, Phoenix, USA
[5] Computational Social Sciences, The University of Chicago, Irvine, USA

[*] **Corresponding author**: Xinyu Zhao (Email: lution798@gmail.com)

Abstract: Gallbladder cancer is the most common malignant tumor in the biliary system. It has the characteristics of low early diagnosis rate, strong invasiveness and high lymphatic metastasis rate. In recent years, with the rapid development of artificial intelligence technology, relevant technologies based on machine learning and deep learning algorithms have been applied to the diagnosis and treatment of malignant tumors, prognosis assessment and medical image processing, bringing revolutionary changes to the diagnosis and treatment mode of malignant tumors. At present, artificial intelligence technology has been preliminarily studied in the early screening and diagnosis of gallbladder cancer, preoperative lymph node status assessment, intraoperative lymph node dissection, surgical treatment and prognosis assessment, showing certain clinical value. In this paper, in order to assist clinical diagnosis of gallbladder cancer, an improved 3D-DenseNet was used to establish an assisted diagnosis model of gallbladder cancer based on enhanced CT images of patients. Firstly, multiple arterial CT images of patients were converted into 3D images, and the regions of interest were cut out using the gallbladder area marked by doctors. Then, the traditional Dense Net network is optimized, the Dropout mechanism and Soft max loss function are improved, and the cross-entropy function is replaced by Focal loss in the output part for imbalance correction, so as to establish the auxiliary diagnosis model of gallbladder cancer.

Keywords: Gallbladder Cancer; Artificial Intelligence; Machine Learning; Deep Learning; Diagnosis.

1. Introduction

Gallbladder carcinoma (GBC) is the most common malignant tumor in the biliary system, ranking the 6th in the incidence of gastrointestinal malignancy, with the characteristics of high malignant degree, strong invasion and easy to occur lymph node metastasis [7]. In recent years, the incidence of GBC has shown a gradual upward trend worldwide, and the incidence of the Chinese population has increased by 20% to 100% in the past 30 years, with about 52,800 new cases per year. In 1956 John McCarthy at Dartmouth conference for the first time put forward the "artificial intelligence" (AI) concept. [1-3]

AI uses machines to simulate the way the human brain thinks and intelligently process primitive problems. With the rapid development of AI technology, the subfields dominated by machine learning and deep learning algorithms have been applied to the auxiliary diagnosis and treatment of malignant tumors, prognosis assessment and medical image processing. In medical image processing, image omics builds disease prediction models by combining AI core technologies such as different machine learning algorithms, providing more information for accurate diagnosis and individualized treatment of diseases.

2. Related Work

Gallbladder cancer can directly invade the surrounding tissue, but also can be transferred through lymphatic, blood circulation or abdominal transplantation and other ways, due to the lack of early clinical manifestations, most cases have been diagnosed in the late stage, serious[8].

Affects patient prognosis. Imaging examination is widely used in the detection of a variety of diseases, among which enhanced CT can well judge the intensity and enhancement mode of the lesion, and can also judge the type of the lesion, which is of great help to clinical diagnosis and treatment[9]. Imaging examination often requires doctors with professional knowledge to identify and judge, which consumes a lot of time and energy, and there is subjective bias among different doctors.

With the continuous development of artificial intelligence, deep learning technology based on neural network is widely used in the field of medical imaging[10-11]. For example, Wu Shi yang et al first segmtioned lung cancer CT images in the lung image database Consortium to obtain lung nodule images, then used Convolutional Neu-ral Network (CNN) for feature extraction, and finally used Logistic classifier for model construction and testing. The classification accuracy of this method is 84.4%. Wu Yun feng proposed a lung CT image classification and system construction method based on improved Inception-Res Net, which has a diagnostic accuracy of over 95% for COVID-19. Ye Jia chao et al[12]., based on the Dense Net network model in CNN, achieved a good recognition effect on CT images of COVID-19, with an accuracy rate of 91%, a recall rate of 79%, an F1 value of 85%, an accuracy rate of 85% and an AUC value of 94%.

In this paper, we optimized and improved the Dense Net model, increased the traditional 2D image input to 3D, improved the Dropout mechanism and Soft max loss function, and applied the improved 3D-DensenET model to the auxiliary diagnosis of gallbladder cancer [13-14].

3. Model and Methodology

DenseNet is the optimal depth model proposed by Huang Equal in 2017, which uses the advantages of ResNet and GoogLeNet for reference and fully applies cross-connection to each feature layer in the module, that is, the input of any convolutional layer directly includes the output of all previous convolutional layers, and the features are fully reused.

3.1. DenseNet Model

The feature fusion of high and low levels makes the network have strong anti-overfitting performance, and the number of parameters is smaller. The cross-connection application also alleviates the problem of gradient disappearance caused by the deepening of layers. DenseNet is Dense by multiple

DenseNet is a convolutional neural network with dense connections. The network consists of two parts: DenseBlock and Transition. Dense Block is a densely connected highway module, a collection of Bottleneck Layer outputs. block and Transition layer, each Dense block contains multiple substructures, a structure of 4 Dense blocks.

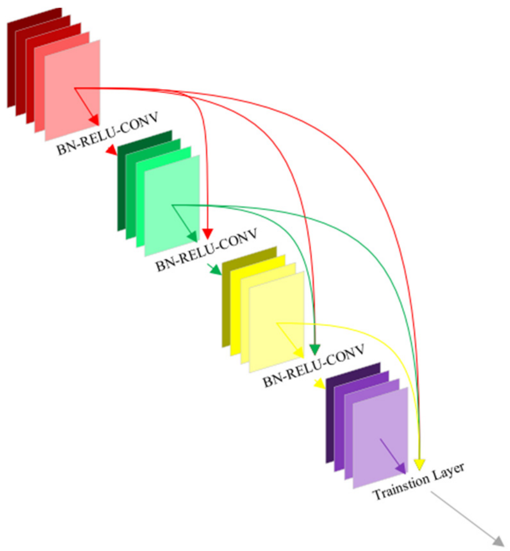
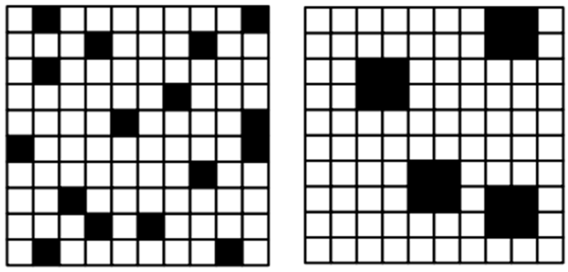


Figure 1. 4-layer Dense block structure

The traditional DenseNet structure contains the Dropout layer, which inhibits model overfitting by randomly dropping multiple neurons. CNN extracts image features through convolution check. The specific implementation of the convolution operation generates information redundancy between feature images, so the effect of Dropout on CNN is limited. The DropBlock module is a regularization module for CNN proposed by the Google team in 2018. Effect comparison of Dropout and DropBlock.

In order to verify the performance of this model, 3D-RESnet and 3D-Densenet models with various structures and different parameters were analyzed and compared, and the most suitable 3D CNN for gallbladder cancer classification was selected.

In traditional convolutional networks, when the output features of a previous layer are needed by the input layer at the back, they need to be convolved and then extracted again. However, DenseNet's dense connections do not need to be extracted again and can be directly used by the layer at the back, which greatly reduces the consumption of parameters and the amount of calculation. In this paper, it is selected as the main body network of shot boundary detection.



(a) Dropout (b) DropBlock

Figure 2. Effect comparison between dropout and dropblock

The 3DDenseNet proposed in this paper mainly consists of Conv3D, Max-pooling, 6 SB d blocks, 6 SBDBlock2, 8 SBDBlock3, 8 SBDBlock4 and Linear. The structure is shown in Figure 1, and the model parameters are shown in Table 1. Each SBD Block contains Dense Block dense connections and new Conv3D additions, followed by a BRA module containing Batch Normal iza-tion, RELU, and Avg pooling. Finally, Linear layer outputs 3 types of features.

Table 1. The model parameters of3D DenseNet

Layer	**Kernel**	**Feature map**	**Followed by**
Input	--	8×3×16×128×128	--
Cov 3D	7×7×7	8×64×16×64×64	BN,RELU
Maxpooling	3×3×3	8×64×8×32×32	BN,RELU
SBD Block1	--	8×32×8×32×32	BRA
SBD Block2	--	8×32×4×16×16	BRA
SBD Block3	--	8×32×2×8×8	BRA
SBD Block4	--	8×32×1×4×4	BRA
Linear	--	1×3	--

In this paper, the cross entropy loss function is selected as the loss function of 3DDenseNet, and the formula of the cross entropy loss function is:

$$L=-[y\log y+(1-y)\log(1-y')] \quad (1)$$

Make the predicted data distribution more closely resemble the real data distribution. Set the compression coefficient θ to 0.5, growthrate to 32, and learning rate to 0.001.

Finally, after the post-processing step, the color histogram method is used to detect the merged gradient frame segment again, which not only improves the detection accuracy of the gradient frame segment, but also speeds up the detection speed [15].

3.2. Model Architectures

Model evaluation indexes include Accuracy, Speci-ficity, Sensitivity, Precision and ROC curve. The calculation formula of each index is shown as follows:

$$accuraty = \frac{TP + TN}{Z + C}$$
$$specificity = \frac{TN}{FP + TN} \quad (2)$$

$$sensitivity = \frac{TP}{TP + FN}$$
$$precision = \frac{TP}{TP + FP} \quad (3)$$

The number of patients with cystic cancer identified by the target detector as benign gallbladder disease; True Negatives

(TN) represent the number of patients with benign gallbladder disease identified as non-gallbladder cancer by the target detector. Z represents the number of gallbladder cancer patients; C represents the number of patients with benign gallbladder disease.

Receiver Operating Characteristic Curve (ROC curve) is a curve drawn according to a series of different binary classification methods (boundary value or determination threshold), with true positive rate (sensitivity) as the vertical coordinate and false positive rate (specificity) as the horizontal coordinate. AUC (AreaUnder Curve) is the area under the ROC curve. Scholars often use the AUC value as the model evaluation criterion, and the ROC curve cannot clearly explain which classifier has the better effect, while the classifier with the larger AUC value has the better effect.

4. Conclusion

The onset of gallbladder cancer is insidious and most of the early stage is asymptomatic, so when patients find, the lesion has already developed to the advanced stage, patients often lose the opportunity for treatment because of the late stage of the tumor. Clinical diagnosis of gallbladder cancer mainly relies on traditional imaging, such as dual-source CT. However, the recognition of abdominal dual-source CT images requires doctors to have rich professional knowledge and experience in reading the images. Manual reading not only consumes a lot of time and energy, but also may cause misjudgment due to negligence or subjective factors.

Deep learning algorithm has the characteristics of strong learning ability, wide coverage, good adaptability and high upper limit. Therefore, based on the deep learning model, this paper realizes the diagnosis of gallbladder cancer by extracting image features. Experimental verification shows that this model has certain feasibility in the diagnosis of gallbladder cancer. However, at present the model is still

There are the following problems:

1) The data of gallbladder cancer is small. For medical image research, the construction of data set is a very important part, but medical data often has problems such as difficult collection, sensitive information and unconcentrated distribution.

2) The interpretability of deep learning model has been criticized for a long time. Currently, the gold standard for diagnosing gallbladder cancer is pathological examination.

Therefore, this paper proposes a depth shot boundary detection method combining 3D convolution and DenseNet, which uses 3D convolution to capture the characteristics of temporal and spatial information and extract video features to a greater extent. DenseNet dense connection reduces parameter calculation, realizes feature reuse, and improves efficiency. Experiments and comparisons on the commonly used UCF101_SBD and TRECVID datasets and ClipShots, the largest shot boundary detection dataset, show that the proposed method has good detection effect and improves detection efficiency.

However, the model proposed in this paper is constructed based on the preoperative image data of patients, and the image data alone cannot completely accurately determine whether a patient is a gallbladder cancer patient. In addition, the specific meaning of the deep features extracted by deep learning cannot be explained, and subsequent work will consider adding some interpretable features. In summary, the gallbladder cancer diagnosis model proposed in this paper based on the improved 3D-DenseNet has good accuracy and reliability, and large-scale multi-center experiments will be conducted in the future to promote the application of this model in clinical assisted diagnosis.

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