ISSN: 2414-1895 DOI: 10.6919/ICJE.202209_8(9).0049

Application of Deep Learning in the Diagnosis of Lung Nodule Classification

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Abstract

Lung cancer is a malignancy with the highest mortality rate, and early diagnosis and detection of lung nodules is the key to reducing the mortality rate of lung cancer patients. Deep learning techniques have the advantage of automatically extracting nodule features, self-learning and automatically classifying the benignity and malignancy grade of lung nodules, and computer-aided diagnosis techniques based on this have shown great potential in the early confirmation of lung nodules. This paper firstly introduces commonly used lung imaging datasets, followed by the applications of 2D convolutional neural networks, 3D convolutional neural networks, combined 2D and 3D techniques and generative adversarial networks in lung nodule classification, and finally analyses deep learning methods for lung nodule classification and provides an outlook on future research directions.

Keywords

Lung Nodules; Deep Learning; Computer-aided Diagnosis; Convolutional Neural Networks; Lung Imaging.

1. Introduction

Lung cancer is one of the most dangerous malignant tumours to human health in worldwide, with approximately 1.77 million deaths from lung cancer worldwide each year[1]. Lung nodules are a symptom of the early stages of lung cancer[2]-, so screening and clinical consultation for the detection of lung nodules is extremely important to accurately identify their benignity and malignancy to help determine the best treatment period and improve the survival rate of lung cancer patients. Low-dose computed tomography(CT)[4] is a commonly used clinical technique for effective detection and diagnosis of nodules and is an effective screening method for asymptomatic early stage lung cancer, detecting 90% of lesions[5], The use of this technology enables the timely detection of lung nodules and gives a better reference for patient treatment. At the same time, the number of CT scans of the patient's lungs is enormous and the clinical imaging physician needs to devote a great deal of work effort to providing a clinical diagnosis based on the lung nodules found in the CT images. The long hours of manual lung nodule screening not only make it easy for the physician to make incorrect screening results but also inefficient. Computer-aided detection (CAD) has been introduced to screen nodules in the clinical setting in order to take advantage of the physician's expertise in identifying nodules and to significantly reduce the number of lung images read. The use of traditional computer-aided diagnostic techniques for the diagnosis of lung nodules has many shortcomings, such as inconsistent detection and classification methods, classification accuracy needs to be improved, high false-positive nodule detection results and no self-learning capability. In contrast, computer-aided

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diagnostic techniques based on deep learning are now increasingly used in the diagnosis of pulmonary nodules, with significant improvements in speed and accuracy of reading, and the ability to continuously optimise the results through self-learning, In order to provide a reference for future work in the field of research related to the classification and diagnosis of lung nodules, this paper focuses on the introduction of the dataset, the application of lung nodules in convolutional neural networks and generative adversarial networks for classification and diagnosis, the deep learning algorithms proposed in the classification of lung nodules and the effectiveness of their application, pointing out the problems with the current technology and providing an outlook on future trends.

2. Lung Imaging DatasetS

Datasets are an important part of deep learning algorithms, and the quality of the dataset images and the integrity of the lung information contained determines the accuracy and robustness of the trained deep learning algorithm, therefore, several commonly used publicly available datasets are presented.

2.1 LIDC-IDRI

The Lung Image Database Consortium (LIDC-IDRI)[9] is one of the most authoritative public lung cancer screening databases. 1018 chest CT scans from 1010 patients are included in the LIDC-IDRI dataset, which is stored in DICOM format with a pixel value of 512 x 512 and an image thickness range of 0.5 to 5 mm. Each case in the LIDC-IDRI dataset consists of hundreds of images and an Extensible Markup Language (XML) file. The XML file records detailed information about the lung lesion, including nodule location, margins, texture and other information. Experts classify the detected lung lesions labelled nodules into four categories, including unknown, benign, primary lung cancer and metastatic lesions. The LIDC-IDRI is a common dataset for accurately assessing the performance of computer-aided diagnosis and is widely used.

2.2 NLST

The National Lung Screening Trial (NLST)[10] is a collection of the US National Screening Trial database completed in 2009. The dataset consists of low-dose CT images and chest radiographs, providing over 75,000 images of CT screening and 1,200 pathology images of lung cancer patients. In addition, the NLST provides data on participant screening results, diagnostic procedures, presence of lung cancer and mortality rates. The aim is to determine whether screening for lung cancer by low-dose spiral CT, as opposed to conventional chest radiography screening, can reduce lung cancer mortality in high-risk groups.

2.3 JSRT

The Japanese Society of Radiology Technology (JSRT)[11] database is a standard public digital image database published by the Japanese Society of Radiology Technology. 247 CT images were included in the JSRT database, 154 of which had pulmonary nodules and 93 without. Each CT image is 2048 x 2048, with 4096 grayscale pixels and lung nodule diameters ranging from 5 to 40 mm. all lung CTs contain information such as the patient's age, diagnosis, and nodule coordinates. The database can be used for image classification based on deep learning techniques, image segmentation, regression analysis, super resolution, etc.

2.4 LUNA16

The Lung Nodule Analysis 2016 (LUNA16)[12] dataset is derived from the database LIDC-IDRI and is composed of 888 low-dose CT images from 1018 CT images, after removing slices thicker than 3 mm, incomplete slices and cases with nodule sizes larger than 3 mm. lUNA16 provides information on the location of lung nodules and diameter size.

3. CNN-based Classification of Lung Nodules

The basic structure of a Convolutional Neural Network (CNN) consists of five parts: an input layer, a convolutional layer, a pooling layer, a fully connected (FC) layer, and an output layer. This section

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introduces the application of Two Dimension Convolutional Neural Network (2D-CNN), Three Dimension Convolutional Neural Network (3D-CNN) and the combination of 2D-CNN and 3D-CNN in nodule classification.

3.1 2D-CNN

The meaning of 2D-CNN includes two aspects, the convolution kernel of the CNN is a 2D convolution kernel or the input of the CNN is a 2D sliced image, the structure of which is shown in Figure1. Although the 2D-CNN framework loses the stereoscopic information of the nodules, some methods use the relationship between adjacent slices to still preserve the 3D information of the nodules.

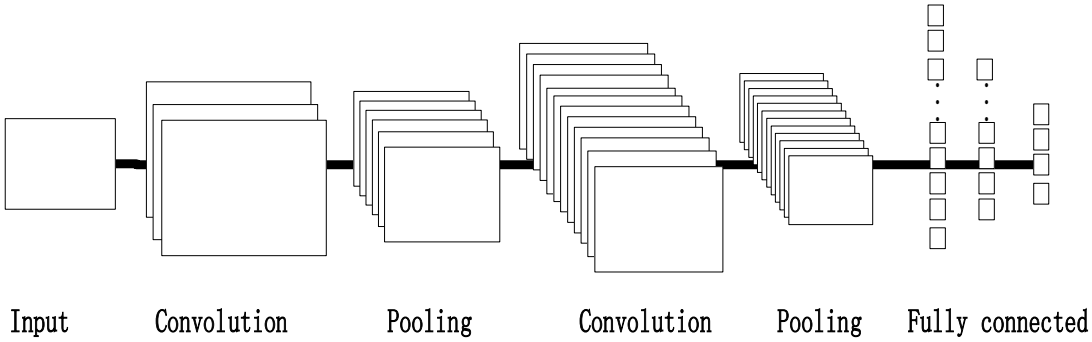

Figure 1. 2D-CNN model structure

In 2015, 2D-CNN was applied to lung nodule classification for the first time in a computer-aided diagnosis system, solving the problem that traditional lung nodule classification is not stable enough and cannot continuously improve the accuracy rate[13]. The dataset used was LIDC-IDRI containing 1018 CT images. 2545 images of lung nodules larger than 3 mm in diameter were selected from the database for the experiment, and the results showed that the sensitivity of the method for lung nodules was 73.3% and the specificity was 78.7%. The experimental results show that the deep learning technique improves the efficiency while the classification effect is better than that of the traditional classification method of computer-aided diagnosis system. A multi-resolution 2D-CNN was transferred and reconstructed using a knowledge transfer[14] approach[15]. The knowledge transfer method allows knowledge from the source model to be transferred to the target domain so that the target domain retains the same primary structure as the source model. Lung nodule candidate regions are mapped in the network model as features of different resolutions and scales, and the method can be successful in identifying some less obvious lung nodules caused by radiological heterogeneity. The accuracy measured on the dataset LUNA16 with the generated sample set was 97.33%, showing that the classification outperformed most of the classification methods, but the network model was not able to capture contextual information between sequence slices.

As most medical images are 3D images containing important spatial information, 2D-CNN mainly adopts the method of 2D slicing for classification, which cannot effectively use the 3D information of CT images, but has the advantages of simple network structure and short computation time. The improvement work for the shortcomings of 2D-CNN can be focused on how to achieve the extraction of spatial information through 2D convolutional kernels, which can appropriately reduce the computational resource overhead of the classification network.

3.2 3D-CNN

Compared to 2D-CNN, 3D-CNN uses 3D convolutional kernels, so for the use of medical images of lung nodules, 3D-CNN is able to extract more potential feature information contained in 3D images, which helps to improve the classification accuracy and give correct diagnosis results, the 3D-CNN structure is shown in Figure 2.

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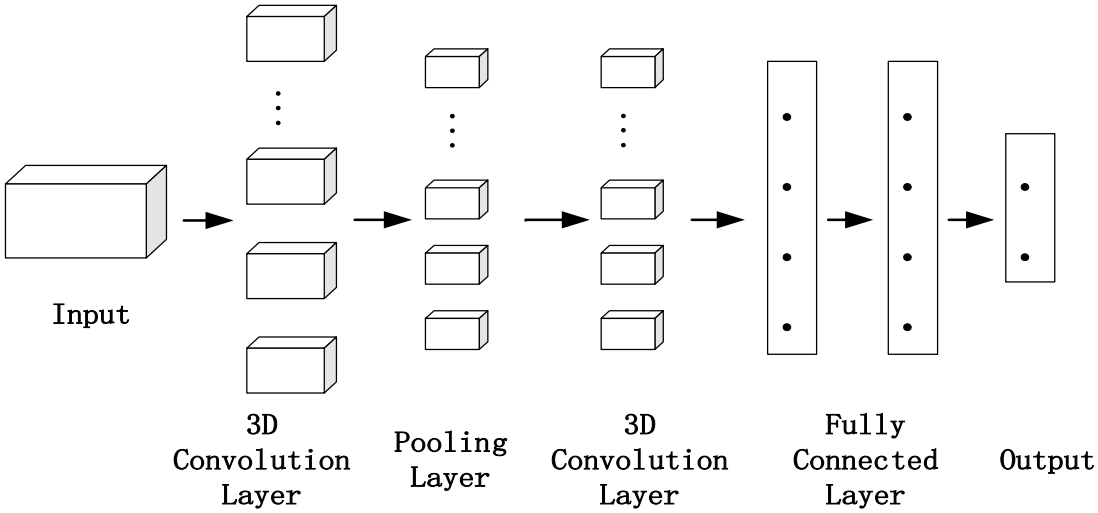

Figure 2. 3D-CNN model structure

A 3D-CNN algorithm based on the lung nodule level was investigated for data expansion techniques and modifications to the network training cost function in order to address the imbalance between benign and malignant samples in the data[16]. The literature provides a comprehensive evaluation of 3D-CNN architectures, focusing on three 3D -CNN architectures with different input sizes and number of layers. The results of the study show that the best results are obtained with an input size of 32×32×32 pixels, 2 convolutional layers and 2 pooling layers. The accuracy in the dataset LIDC-IDRI test was 91.88%. To solve the multi-scale structure problem fusing local and global neural networks for the prediction of nodal malignancy[17]. In the paper, the extraction of local and global features of medical images is performed by residual convolution and non-local convolution. The area under the curve (AUC) of the method is 95.62% and the results show that the combination of local and global neural networks helps in the extraction of multi-scale features. Based on Multi-Depth-Residual Attention Networks (MDRA-Net), feature fusion and iterative hierarchical fusion were used to improve the network's ability to sense nodule location features and global features[18], and the sensitivity and specificity of the model in detecting nodules on the LUNA16 dataset were 93.01% and 97.77%. An attention mechanism-based three-dimensional bidirectional feature fusion network for pulmonary nodules is proposed, inspired by the Dual Path Networks(DPN) in nodule classification[19]. The introduction of a spatial attention learning mechanism solves the problem of uneven representation of lung nodules throughout 3D space and further balances the true positive rate with the false positive rate. The RAN module was introduced into Dual Path Networks to ensure the integrity of the acquired features and filter redundant features[20]. The improved model was evaluated on the dataset LIDC-IDRI, and the F1-score reached 91.0%, indicating the great advantage of DPN CNN in acquiring nodal features. A multi-task learning approach is introduced in the dual-path CNN to construct a model combining a multi-stream convolutional neural network structure, a residual network structure and a multi-task learning network structure[20][19]. Multiscale feature fusion enables the network to enhance the focus on the background information of lung nodules and improves the generalisation ability of the network, and multi-task learning fuses the grading of different attributes into the classification task to improve the classification performance of the network. A 3D-Unet self-supervised learning network model is proposed to address the problem that a large number of annotated samples are required for the training of deep learning models, but the available annotated data in the medical field is insufficient. Self-supervised learning can be performed by combining only partially annotated data, thus improving the classification performance of 3D lung nodules, with an accuracy of 88.6% and an AUC value of 92.9% on the publicly available dataset LIDC-IDRI. A 3D anisotropic convolution-based network for classifying benign and malignant lung

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nodules is proposed to address the problem of different resolution of images acquired by different CT devices[23]. It splits the 3D convolution into two 3D anisotropic convolutions of k×k×1 and 1×1 ×k and proposes a cropping-non-local pooling module to solve the problem of different resolutions and enhance the feature extraction of the nodule region by the network, and the classification accuracy of the model is 91.53%.

The 3D-CNN can fully extract feature information of nodules, which improves the classification effect to a certain extent, but the 3D convolutional kernel increases the complexity and training time of the network compared with the 2D convolutional kernel, which increases the computational cost to a certain extent.

3.3 Combining 2D-CNN and 3D-CNN

The 2D-CNN model has a simple structure, but is not comprehensive enough for feature extraction of medical images with 3D slices, and the spatial information is not fully utilised. The 3D-CNN model can improve the utilisation of images and the accuracy of lung nodule classification to a certain extent, but also increases the number of parameters and the detection speed is not fast enough. Based on this, a model combining 2D-CNN and 3D-CNN to process different stages of image information separately can both reduce the complexity of the model and make full use of the characteristic information of 3D images. A weighted fusion multidimensional convolutional neural network model for lung nodule classification is proposed[24]. The model consists of two sub-models: a multi-scale dense convolutional network model based on 2D images to capture a wider range of nodule features, and a 3D convolutional neural network model based on 3D images to make full use of nodule spatial contextual information. Sub-models are trained using 2D and 3D CT images, their weights are calculated based on the sub-model classification errors, and the sub-model classification results are weighted and fused to obtain the final classification results. The model achieved a classification accuracy of 94.25% and an AUC value of 98% on the public dataset LIDC-IDRI. A decision-level based Multi-Dimensional Fused network (MDF-Net) and a Multi-output Multi-Dimensional Fused network (Mo MDF-Net) were designed[25]. The MDF-Net network fine-tunes the features of 2D lung nodule slices extracted from different perspectives, extracts the features of cross-sectional 3D lung nodule slices, and the Mo MDF-Net network performs multi-scale feature extraction at the input level, while fusing feature maps with different levels of semantic information at different stages. The experimental results show that the proposed multidimensional information fusion network effectively solves the problem of benign and malignant lung nodule classification, obtaining better classification results than the separate 2D or 3D neural network design approaches, in addition, the network requires fewer training parameters than the 3D convolutional neural network.

4. Pulmonary Nodule Classification based on Generative Adversarial Networks

Generative adversarial networks (GAN) [26] consist of a generator (G) that generates new image samples and a discriminator (D) that distinguishes between estimated samples from real samples and generated samples. The GAN is able to generate images with similar features to the input image, solving the problem of increased training difficulty due to insufficient number of samples. A GAN-based deep convolutional generative adversarial networks (DCGAN) model generates lung nodule images with similar texture features as the input images, and uses these images to train the DCGAN model[27]. In this paper, authors improved the image source classification into image source classification and class classification of lung nodules, which effectively solved the problem of imbalance between benign and malignant data and enhanced the noise immunity of the DCGAN model and the class classification of lung nodules. The accuracy of the model in classifying benign and malignant lung nodules was 80. 13%. The experimental results show that this model has good classification effect, high accuracy and good noise immunity. A generative adversarial network incorporating DCGAN and asserstein GAN-gradient penalty (WGAN-GP) was used to generate clear images as expanded samples using a progressive training model[28]. The accuracy, sensitivity, specificity and AUC values of this joint model for the classification of benign and malignant nodules

in lung CT images reached 96. 5%, 96. 67%, 96. 33% and 95.3%, and relevant reference experiments were designed to validate the feasibility and effectiveness of using generative samples from generative adversarial networks to improve the capability of the lung nodule benign-malignancy classification model.

5. Summary and Outlook

With the continuous advancement of deep learning technology, automatic assisted diagnosis systems based on deep learning are playing an increasingly important role in the medical field, and the related assisted detection systems have achieved better results in the detection and classification of lung nodules. From the extraction of planar features from two-dimensional images to the design of three-dimensional neural networks that make full use of spatial information, and then to the use of deep convolutional generative adversarial networks composed of convolutional networks to solve the problem of sample imbalance in the dataset, the structure of classification networks has been continuously improved, relevant theories have been perfected, and model parameters have been continuously optimized, and the effect of deep learning applied to the benign and malignant classification of lung nodules is remarkable. However, there are also some shortcomings, such as the lack of image data, the failure of related techniques to be applied to clinical practice on a large scale, and the differences in image quality of scans from different devices.

In future research, the following outlook is made on the classification of benign and malignant lung nodules and the classification of malignant grades. Better neural network parameters are trained using migration learning techniques, and then network models suitable for lung nodule classification are trained through migration learning, and the application of migration learning is expected to make up for the shortcomings of insufficient data sets and train automatic assisted diagnosis systems with higher accuracy using limited medical data; in the academic, With the joint efforts of academia, medicine and industry, the new computer-aided diagnostic system will be integrated with major information systems in hospitals to promote the application of intelligent assisted detection systems in medical clinics; Combining the hardware advantages of cloud computing with big data, it breaks through the limitations of hardware that prevent efficient model training or model performance verification, while solving the problem of insufficient data sets.

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