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A Short Contemporary Survey on Covid-19 Diagnosis

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Abstract

As the new crown pneumonia epidemic continues to worsen, traditional diagnosis cannot satisfy the demand of the detection of disease. Therefore, it becomes necessary to use artificial intelligence to assist medical treatment to achieve efficient and accurate judgments. At present, deep learning is becoming more and more mature in the domain of medical image, which is capable to offer quicker, cheaper and safer diagnostic service for the person infected by COVID-19. This paper offers a comprehensive summary of the latest approaches and applications of deep learning in the domain of COVID-19. We summarized and analyzed some COVID-19 detection methods and models. Through research and analysis, deep learning can provide accurate and efficient diagnosis for COVID-19 classification.

Keywords: COVID-19; Classification; Deep learning.

1. Introduction

In traditional virus detection, each suspected case needs to be verified by RT-PCR(Reverse Transcription-Polymerase Chain Reaction) [1]. But it takes a lot of time to perform RT-PCR, and the false negative rate is high [2]. CT (Computed Tomography) images and X-ray images are useful for medical evaluation of pulmonary imaging and treatment in people infected with COVID-19. Chest CT images and X-ray images provide a wealth of pathological information, but the lack of computers to accurately quantify infected areas and its pathological changes has hindered healthcare providers from providing diagnostic screening quickly. Feng Yu et al. [3] proposed a lung nodule recognition approach which is based on a three-dimensional convolutional neural network considered lots of false positives in lung nodule detection in traditional computer-aided detection systems. Ma Yuan et al. [4] used deep belief nets to identify benign and malignant lung nodules in CT images. Huang Sheng et al. [5] proposed a CT image pattern classification model more suitable for lung tissue based on the improved deep residual network.

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Artificial intelligence is used to rapidly analyze case characteristics, detect CT and X-ray chest images for any abnormalities, and provide clinicians with further diagnosis for treatment or isolation. Shalu C et al. [6] adopted convolutional neural networks to recognize motion image formation task, but did not consider the influence of hyperparameters with classification performance. Ma M et al. [7] presented the k-means clustering initialization hyperparameter algorithm, which improved the accuracy of network recognition and accelerated the network training process. Ijjina E P et al. [8] used genetic algorithm to improve the hyperparameters of the network to minimize classification error. The hyper-parameter automatic selection method refers to the calculation and statistics method in the selection process using the high-performance accelerated model. Bayesian optimization is employed to automatically search for best hyper-parameters of deep convolution to configure the network. Wang Y et al. [9] adopted PSO algorithm to optimize and modify the structure of CNN and determine the configuration of hyperparameters. Although the current optimization algorithms can exhibit different optimize ability, complexity, exploratory efficiency, hyper-parameter optimization is always deserved to research and exploration.

2. Methods and Results

The development of AI-based automated CT and X-ray image analysis tools for coronavirus detection, quantification, and tracking is essential for epidemic control. There have been some studies on COVID-19 screening and prediction tasks, which mainly use deep learning model to extract features and achieve classification task of CT images and X-ray images to distinguish coronavirus patients from non-patients. In this way, a non-contact method based on pathological principles can be used for COVID screening, and the risk of doctors being infected by patients is reduced [10]. In deep learning [11-13], there are many network structures that can be used to achieve COVID-19 classification. Such as ResNet, VGG, DenseNet, Inception, GoogleNet, MobileNet, Xception, etc. The classifiers include SVM, ELM, Softmax, etc.

Traditional network structure has good performance for the classification and recognition of new coronary pneumonia. Wang et al., [14] implemented an automated deep learning system for coronavirus diagnosis and prognosis analysis. This experiment was carried out on two data sets. The highest sensitivity and maximum specificity of the experiments in the two data sets were 80.3% and 81.1%. What they use is the DenseNet network. DenseNet directly connects layers to enhance feature transfer and make more efficient use of features. Li et al. distinguished between community-acquired pneumonia and new coronary pneumonia on chest CT. Sensitivity was 90% and specificity was 96%. They use the ResNet-50 residual network, which uses skip-connected residual blocks to alleviate the problem of vanishing gradients, so it is easier to build a deeper network to improve performance. Saiz and Barandiaran, [17] adopted deep learning methods to achieve coronavirus disease detection in chest images of x-ray. Accuracy is 94.92%, sensitivity is 94.92%, and specificity is 92%. The network they use is VGG network. The deep network structure, small convolution kernel and pooling sampling domain of the VGG model enable it to get more features while controlling the quantity of parameters, thereby avoiding too much calculation and too complicated structure. The VGG model performs well in multiple transfer learning tasks. Wu et al., [23] also used the VGG-19 network to screen and diagnose COVID-19. Its disadvantage is that there are too many parameters and more storage space is required. Waheed et al., [18] used the auxiliary classifier GAN to enhance data and improve COVID-19 detection. Accuracy is 95%, sensitivity is 90%, and specificity is 97%. Song et al., et al., [20] realized the end-to-end automatic identification between coronavirus disease and viral pneumonia. Sensitivity was 85% and specificity was 88%.

In addition, there are some new network structures for the identification of coronavirus disease which have achieved good performance. Ni et al., [16] proposed a DL method to describe the features of pneumonia in chest images of CT, with a sensitivity of 100%, and a sensitivity of 0.96% for detecting each patient with lung disease. The models used are MVP-Net and 3D U-Net. Apostolopoulos et al., [21] used the MobileNetV2 network for COVID-19 classification and identification. MobileNet is a new model based on deep separable convolution, which has advantages in scale, calculation and speed. Das et al., [22] uses Truncated inceptionNet network for filtering (diagnosis). Wu et al., [24] used WRE and proposed a 3SBBO to achieve the target. Wang et al. [25] presented a fusion of GCN and FGC for the classification. Satapahty et al. [26] presented a five-layer CNN (5l-CNN) to diagnosis images. Zhu et al. [27] adopted an ANC network to identify COVID-19. Zhang et al. [28] presented a MIDCAN method that fuse both CT images and X-ray images to diagnose the coronavirus disease.

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3. Discussion and conclusion

COVID-19 identification [29-31] is a classification task. The method used to assess classification performance included Precision, Recall, Sensitivity, Accuracy, F1 Score, etc.

Precision is the proportion of correct judgment in all positive samples.

$$Precision = \frac{TP}{TP+FP} \tag{1}$$

Sensitivity refers to the proportion of all correctly predicted positive samples to all actual positive samples, which is used to measure the ability to recognize positive examples.

$$Sensitivity = Recall = \frac{TP}{TP+FN} \tag{2}$$

Specificity refers to the ratio of all negative samples accurately predicted to all actual negative samples, which is used to measure the ability to recognize negative samples.

$$Specificity = \frac{TN}{TN+FP} \tag{3}$$

Accuracy refers to the percentage of the number of samples that are correctly predicted in all experiments.

$$accuracy = \frac{TP+TN}{TP+FP+FN+TN} \tag{4}$$

F1 Score is the harmonic average of the accuracy and recall of the model.

$$F1 = \frac{2 \cdot Precision \cdot Recall}{Precision+Recall} \tag{5}$$

In this article, we describe several methods for COVID-19 identification using the images of CT and X-ray. In addition, we summarize the characteristics of these methods in

Table 1.

Table 1 Some deep learning algorithms for COVID-19 diagnosis and detection

Author	Method used	Model	DataSet	Results	Aim of study
Wang et al., [14]	Deep learning(DL)	DenseNet121-FPN	5372 (two datasets)CT images	sensitivity: 80.3% and 79.35%, specificity: 76.3% and 81.1%	Diagnosis and prognosis
Li et al., [15]	DL	ResNet-50 as backbone of main mode	4356 CT exams from 3322 patients	Sensitivity: 90%, specificity: 96%	Diagnosis
Ni et al., [16]	CNN	3D U-Net, MVP-Net	14531 Images of CT	Lobe lesion: 0.96%, sensitivity: 100%	Detection

Saiz and Barandiaran,[17]	DL	transfer learning with VGG-16 SDD	1500 Images of X-ray	sensitivity: 94.92%, Accuracy: 94.92%	Detection
Waheed et al., [18]	GAN	VGG-16 and ACGAN3	1124 images of X-ray	sensitivity: 90%, Accuracy: 95%	Detection
Mei et al., [19]	DL	Inception_ResNet_V2	905 Images of CT	Accuracy: 68%	Diagnosis
Song et al., [20]	DL	BigBiGAN1	227 Images of CT	Specificity is 88%, Sensitivity is 85%	Detection
Apostolopoulos et al., [21]	DL	MobileNetV2	455 Images of X-ray	Accuracy is 99.18%, Sensitivity is 97.36%	Classification (detection)
Das et al., [22]	CNN	Truncated inception net	6845 Images of X-ray	Sensitivity is 88%,	Screening (diagnosis)
Wu et al., [23]	DL	VGG-19	495 Images of CT	Sensitivity is 81.1%, Accuracy is 76.0%	Screening (diagnosis)
Wu et al. [24]	Machine learning	WRE-3SBBO	296 CT images	Sensitivity: 86.40% Specificity: 85.81% Accuracy: 86.12%	Diagnosis
Wang et al. [25]	Deep learning	FGC	640 CT images	Sensitivity: 97.71% Specificity: 96.56% Accuracy: 97.14%	classification
Satapahty et al. [26]	Deep Learning	5l-CNN	640 CM Images	Sensitivity: 93.28% Specificity: 94.00% Accuracy: 93.64%	Diagnosis
Zhu et al. [27]	Deep Learning	ANC	640 CT images	Sensitivity: 95.88% Specificity: 96.13% Accuracy: 96.00%	Diagnosis
Zhang et al. [28]	Deep learning	MIDCAN	Both X-ray and CT-images	Sensitivity: 98.10% Specificity: 97.95% Accuracy: 98.02%	Diagnosis

From the Table 1, it can be seen that MVP-Net, 3D U-Net, FGC, MIDCAN, ANC, and the lightweight network MobileNetV2 have relatively excellent performance in COVID-19 classification. In the future, we will discuss more ways to identify COVID-19. There are some other COVID-19 related papers [32-35], we will analyze them in our future studies.

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