

Methods for Supervised Learning in Diagnosis of COVID-19

Subjects: [Computer Science](#), [Artificial Intelligence](#) | [Medical Informatics](#)

Contributor: Tao Zhou , Fengzhen Liu , Huiling Lu , Caiyue Peng , Xinyu Ye

The methods for supervised learning in diagnosis of COVID-19 refer to the samples used for model training being labeled. The label information is fully utilized to guide network model training. The advantage is that the model accuracy can be effectively improved by learning a large amount of label information and the model is easy to evaluate. The current state of deep learning for COVID-19 classification and segmentation tasks from aspects of supervised learning is summarized, including summarizing the application of VGG, ResNet, DenseNet and lightweight networks to the classification task of COVID-19, and summarizing the application of the attention mechanism, multiscale mechanism, residual connectivity mechanism, and dense connectivity mechanism to the segmentation task of COVID-19.

COVID-19

supervised learning

VGG

1. The Classification Methods of COVID-19 Based on Supervised Learning

The classification methods of COVID-19 based on supervised learning refers to use of the supervised learning method in extracting features to train a deep network model to distinguish COVID-19. This section focuses on the application to the COVID-19 classification task of VGG, ResNet, DenseNet, and lightweight networks, as shown in **Table 1**.

Table 1. COVID-19 classification methods based on supervised learning.

Network Name	Modal	Sample Size	Results (%)	Open Source (Y/N)
VGG19 ^[1]	X-ray CT	COVID-19: 4320 Pneumonia: 5856 Normal: 20,000 Lung cancer: 3500	Acc = 98.05 Recall = 98.05 Auc = 99.66 F1 = 98.24	Y
VGG ^[2]	X-ray	COVID-19: 5656 Normal: 5656	Acc = 96.41 Sen = 96.60 Spe = 96.20 Auc = 97.70	N
VGG-16 ^[3]	X-ray	COVID-19: 816 Pneumonia: 867	Acc = 90.00 F1 = 90.00	N

Network Name	Modal	Sample Size	Results (%)	Open Source (Y/N)
		Normal: 948		
Resnet [4]	CT	COVID-19: 631 VP: 417 BP: 518	Acc = 99.62	N
FocusCovid [5]	X-ray	/	Acc = 99.40	
ResGANet [6]	CT	COVID-19: 349 Normal: 397	Acc = 80.00 F1 = 81.00 Auc = 82.00	N
ResGNet-C [7]	CT	COVID-19: 148 Normal: 148	Acc = 96.62 Sen = 97.33 Spe = 95.91	N
3D-ResNet [8]	CT	COVID-19: 1315 Pneumonia: 2406 Normal: 936	Auc = 97.30	N
DenseNet-Tiny [9]	X-ray	COVID-19: 1281 Pneumonia: 4657 Normal: 3270	Acc = 97.99 Pre = 98.38 Recall = 98.15 F1 = 98.26	Y
DenseNet [10]	X-ray	COVID-19: 2431 Pneumonia: 1468 Normal: 13,649	Auc = 94.9 Sen = 90.2 Acc = 80.2	N
AM-SdenseNet [11]	CT X-ray	COVID-19:828 Normal:1000	Acc = 99.18	Y
Corona-Nidnna [12]	X-ray	COVID-19: 245 Pneumonia: 5551 Normal: 8066	Acc = 95.00 Recall = 94.00	Y
InceptionV3 [13]	X-ray	COVID-19: 162 Pneumonia: 4280	Acc = 99.96	N
IST-CovNet [14]	CT	COVID-19: 92,905 Pneumonia: 67,712 Normal: 40,030	Acc = 93.69	N
ML-CAM [15]	X-ray CT	COVID-19: 3254 Normal: 2217	Acc = 94.72	N
CNN + CFS [16]	CT	COVID-19: 349 Normal: 397	Acc = 91.60 Sen = 71.70 Pre = 90.40 F1 = 91.00	N

It is not difficult to see the following summary from Table 4. Firstly, the mainstream classification models are based on ResNet in COVID-19. There are three classification models based on VGG, accounting for 18.75%. There are five classification models based on ResNet, accounting for 31.25%. There are three classification models based on DenseNet, accounting for 18.75%. There are five COVID-19 classification models based on lightweight networks,

accounting for 31.25%. Secondly, public datasets are mainly used for classification method research on COVID19. COVID-19 datasets include X-ray datasets, CT datasets and dual-modality datasets that mix X-ray and CT. About 75% of the COVID-19 dataset come from public datasets and 25% of the COVID-19 datasets come from private datasets. Thirdly, regarding the COVID-19 classification, 30% of the tasks are second classification, 46.66% tasks are third classification. Finally, there are relatively few open source and public code resources about the model. The number of public code resources accounted for 25%, and the number of undisclosed code resources accounted for 75%.

1.1. The Classification Methods of COVID-19 Based on VGG

VGG [17] is a deep convolutional network structure proposed by Simonyan, which consists of five convolutional blocks and the whole network uses a convolutional kernel of fixed size 3×3 . The first two convolutional blocks use two successive 3×3 convolutional operations and the last three convolutional blocks use three successive 3×3 convolutional operations. The advantage of VGG is its simple structure and easy to perform model improvement. VGG improved model performance by deepening the number of network layers and learning more refined deep network features. The main research work of using VGG as the backbone network for COVID-19 classification task is as follows. Ibrahim et al. [1] used X-ray and CT images in VGG19 to provide complementary information for the classification of COVID-19. Elazab et al. [2] extracted the average of advanced features of infected and healthy cases with the help of pre-trained VGG. The extracted features were used as supervisory signals to retrain VGG to reduce the effect of feature space noise and outliers. Danilov et al. [3] achieved the best results with VGG16 in 10 pre-trained networks by generating attention heat maps to supervise neural networks focusing on the objects in the images.

1.2. The Classification Methods of COVID-19 Based on ResNet

ResNet [18] is a convolutional network with residual connection structure proposed in 2015. The feature extraction capability was improved by increasing the depth. However, the gradient disappearance problem leads to a sharp drop in the performance of the model when the network is deepened. The ResNet uses residual connections in the network with the aim of alleviating the gradient disappearance problem in deep neural networks. The residual connections pass the current output directly to the next layer by adding constant mappings between different layers. In the COVID-19 classification task, ResNet is used to alleviate the gradient disappearance problem and improve the classification accuracy of the model. Toğaçar et al. [4] proposed a parallel Resnet network model which uses ResNet-18, ResNet-50, and ResNet-101 to extract different activation sets and improve the classification performance by selecting the dominant activation set. Agrawal et al. [5] added squeezed excitation blocks in residual blocks to enhance lower level feature representation and avoid overfitting by keeping trainable parameters minimal. Cheng et al. [6] improved classification performance by enriching feature information in a single residual block. Yu et al. [7] used the Resnet101 features to underlying relationship between the combined features of graph convolutional neural network to enhance features and improve classification performance. Wang et al. [8] proposed a 3D ResNet-based classification network for COVID-19 in CT images. The residual learning block reduces the complexity of the a priori attention mechanism for transferring the pre-trained detection model.

1.3. The Classification Methods of COVID-19 Based on DenseNet

DenseNet [19] is a convolutional network with dense connections structure proposed by Huang Gao. DenseNet connects all the previous layers to the later layers and each layer receives inputs from all the previous layers [20]. Feature reuse is achieved by feature stitching as the input to the next module. The dense connection helps in back propagation of gradients. DenseNet achieves better performance than ResNet in terms of parameters and computational cost. With DenseNet as the backbone network in the COVID-19 classification task, dense connections pass the feature mapping of the current layer to all subsequent layers. The feature reuse approach reduces the number of parameters and alleviates overfitting. Montalbo et al. [9] used DenseNet as a COVID-19 classification network to reduce the number of parameters by reducing the dense network depth increasing the network width. Park et al. [10] proposed a self-attention mechanism based on DenseNet to achieve COVID-19 X-ray image classification by feeding features into transformer. Li et al. [11] applied spatial attention and channel attention to DenseNet, which improved the objective lesion features and suppressed less relevant features to improve the COVID-19 classification accuracy.

1.4. The Classification Methods of COVID-19 Based on Lightweight Networks

Methods based on the lightweight COVID-19 classification model refer to minimizing the number of parameters without degrading the model performance. The current lightweight networks mainly include SqueezeNet, ShuffleNet, MobileNet, Inception, etc. The size of model parameters can be effectively compressed by using lightweight networks or by introducing deep separable convolution, group convolution or channel shuffling methods. Lightweight methods have received a lot of attention from researchers. The COVID-19 classification method based on lightweight networks can effectively improve the model training speed and facilitate the deployment on mobile devices. Chakraborty et al. [12] designed a lightweight deep neural network, Corona-Nidaan, which uses deeply separable convolution and multiscale convolution kernels. Das et al. [13] truncated a lightweight network model of InceptionV3 using maximum pooling and global average pooling to reduce the feature dimension, the number of parameters and the complexity of computation [21]. Ahmed et al. [14] added an attention module with a one-dimensional vector representation on Inception-ResNet-V2 to evaluate this convolutional neural network and detect COVID-19 using CT images. Owais et al. [15] integrated complementary feature information through multiple lightweight integrated network models to detect COVID-19 from CT and X-ray images. Abraham et al. [16] proposed an integrated lightweight network that invokes correlated feature selection algorithms in multiple networks of Squeezenet, Darknet-53, MobilenetV2, Xception, and Shufflenet to determine the best subset of features to improve the accuracy.

To sum up, the classification methods of COVID-19 based on VGG use different scales and alternating training methods during the training process, which can converge in fewer epochs and alleviate the training time. There are examples of better transferability and strong generalization ability. However, the VGG COVID-19 classification models use three fully connected layers with too many parameters, which leads to large memory and more computational resources. The classification methods of COVID-19 based on ResNet use residual connections to replicate shallow features directly. The gradient disappearance and network degradation problems are solved by

residual connectivity, and the better COVID-19 classification performance is obtained. However, there are more deep layers in ResNet COVID-19 classification model, and it is difficult to optimize; there is a lot of redundant information in this model. The classification methods of COVID-19 based on DenseNet use dense concatenation to transfer shallow layer information directly to the deep layer for further application. The redundancy information is reduced by this model. There are better convergence rates and less parameters at the same network layers. However, when the network layers are increased and features are replicated multiple times, resulting in higher computational complexity and spatial complexity of the model. The classification methods of COVID-19 based on lightweight networks can reduce the number of parameters and the computation in some degree. There are a few lightweight models which are commonly put into use for mobile devices.

2. The Segmentation Methods of COVID-19 Based on Supervised Learning

Image segmentation is an essential task for analyzing medical images and obtaining further diagnostic information in the field of medical image processing. U-net is an image segmentation network structure with classical downsampling and upsampling, which was proposed by Ronnerberger et al. [22]. U-net can obtain accurate segmentation results by employing fewer training samples size. U-net locates COVID-19 lesion regions using deep features and achieves accurate segmentation results using shallow features. This section summarizes the U-net in COVID-19 image segmentation applications combined with attention mechanism, multi-scale mechanism, residual connectivity mechanism and dense connectivity mechanism, as shown in **Table 2**.

Table 2. COVID-19 segmentation methods based on supervised learning.

Mechanism	Network Name	Sample Size	Results (%)	Open Source (Y/N)
Attention mechanism	nCoVSegNet [23]	Slices: 244,537	Dice = 66.80 ESN = 70.70 SPE = 99.75 PPV = 69.77	Y
Attention mechanism	CAD CNN [24]	Slices: 393	Dice = 85.43 Recall = 88.10	N
Attention mechanism	D2A U-Net [25]	Slices: 3949	Dice = 72.98 Recall = 70.71	N

Mechanism	Network Name	Sample Size	Results (%)	Open Source (Y/N)
Attention mechanism	DUDA-Net [26]	Slices: 557	Dice = 87.06 Iou = 77.09 Acc = 99.06 Sen = 90.85	Y
Attention mechanism	RefNet [27]	Slices: 230	Dice = 91.37 Sen = 91.54	N
Multi-scale mechanism	MSD-Net [28]	Slices: 4780	Sen = 90.85 Spe = 99.59	N
Multi-scale mechanism	MPS-Net [29]	Slices: 300	Dice = 83.25 Sen = 84.06 Spe = 99.88 Iou = 74.20	N
Multi-scale mechanism	[30]	Slices: 3929	Dice = 83.25 Iou = 74.20	Y
Multi-scale mechanism	COVID-SegNet [31]	Slices: 165,667	Sen = 84.06 Spe = 99.88	N
Multi-scale mechanism	JSC [32]	Slices: 2885	Dice = 78.50	Y
Residual connectivity mechanism	ResUnet [33]	Slices: 5349	Dice = 85.19 Sen = 84.66 Prec = 84.22	Y
Residual connectivity mechanism	Backbone + Res_dil + Attention [34]	Slices: 473	Dice = 83.1	N
Residual connectivity mechanism	MultiResUNet [35]	Slices: 3520	Dice = 74.28	N
Residual connectivity mechanism	Literature [36]	Slices: 100	Dsc = 94 Acc = 89 Pre = 95	N
Dense connectivity mechanism	SCOAT-Net [37]	Slices: 17	DSC = 88.99 SEN = 87.85	N

It is not difficult to see the following summary from **Table 2**. Firstly, the methods of U-Net combined with the attention mechanism and U-Net combined with the multiscale mechanism were more often adopted in COVID-19

Mechanism	Network Name	Sample Size	Results (%)	Open Source (Y/N)	Mechanism,
			PPV = 90.28		used on a
			Dice = 80.31		used on a
Dense connectivity mechanism	ADID-UNET [38]	Slices: 1318	Pre = 84.76 Spe = 99.66 Auc = 95.51	Y	ed on the ll COVID- COVID-19 . Fourthly,

there are relatively few open source code resources in terms of the models. The number of public code resources accounted for 37.5%, the number of undisclosed code resources accounted for 62.5%.
Note: /: No information found.

2.1. The Segmentation Methods of COVID-19 Based on Attention Mechanism

The segmentation methods of COVID-19 based on the attention mechanism refer to calculating its attention distribution based on the input information and obtaining the context vector to selectively focus on the key information of the lesion region in the COVID-19 image. This method can select the information that is more critical to segmentation task among redundant information and improve the segmentation performance by efficiently selecting segmentation features in COVID-19 images. The attention mechanism has received a lot of attention from researchers since it was proposed and the following work has been done in COVID-19 segmentation lesions. Liu et al. [\[23\]](#) used spatial and channel attention in U-Net to segment COVID-19 lung infections. The problem of boundary unclear and lesions complex was solved by making the upper and lower features combined. Karthik et al. [\[24\]](#) introduced contour attention on the last two decoders to refine the infected region for COVID-19 lesion segmentation. The noise inherent in the coarse contour region is discarded by combining shape and boundary information structural features with depth semantic feature maps. Zhao et al. [\[25\]](#) applied gate attention between encoder and decoder to suppress irrelevant information noise and refine the upsampling features. Xie et al. [\[26\]](#) proposed a model based on expansive attention applied between encoder and decoder to solve the redundancy problem in high-level and low-level feature channels. Kitrungrotsakul et al. [\[27\]](#) proposed an interactive attention in U-Net that emphasizes important sensitive segmentation lesions by using residual attention.

2.2. The Segmentation Methods of COVID-19 Based on Multi-scale Mechanism

The COVID-19 segmentation method based on the multi-scale mechanism refers to the multi-scale features obtained from receptive field for COVID-19 lesion segmentation. The multiscale feature extraction method reduces the loss of lesion edge and spatial location information and improves segmentation performance by combining multiscale feature receptive field information. Scale invariant features are learned without loss of information to improve the segmentation accuracy of weak lesion and boundary. For the problems of different sizes of COVID-19 lesions, blurred boundaries and the gaps between high and low levels, researchers mainly carried out the following work. Zheng et al. [\[28\]](#) proposed a multiscale discriminative segmentation network, MSD-Net, using pyramidal convolution blocks to achieve multiscale sensory fields for input feature maps. Pei et al. [\[29\]](#) used grouped convolution in an encoder to achieve multiscale feature extraction. Bose et al. [\[30\]](#) proposed a deep multiscale segmentation network, in which the deep multiscale module captures multi-spatial dimensional objects based on

acquiring different depth feature maps. Yan et al. [31] proposed a 3D segmentation network, COVID-SegNet, which implicitly enhances the contrast and adaptively adjusts intensity on the feature layer to capture effective features of different scales. Wu et al. [32] enhanced segmentation features by aggregating different scale feature maps from different stages to segment COVID-19 lesions.

2.3. The Segmentation Methods of COVID-19 Based on Residual Connectivity Mechanism

The COVID-19 segmentation method based on the residual mechanism refers to a feature pass by using jump connections in the network cross-layer or using residual blocks to replace the convolutional layer for COVID-19 lesions segmentation. This method improves the feature reuse capability by introducing residual mechanism to ensure the back propagation of gradients and alleviate the degradation problem caused by deep networks. Hu et al. [33] proposed a COVID-19 segmentation network using ResUnet as the backbone to reduce the semantic gap between high and low feature maps. Zhou et al. [34] introduced residual connections in COVID-19 lesion segmentation network of U-Net to improve segmentation performance by integrating segmentation information from different levels. Yang et al. [35] reduced the contextual semantic gap by concatenating the outputs of three series of convolutional layers through residual connections in a jump connection structure. Chen et al. [36] captured complex features from the original image to segment COVID-19 lesions by using a topology of residual connections in U-Net to better learn potential representation of the input CT image.

2.4. The Segmentation Methods of COVID-19 Based on Dense Connectivity Mechanism

The COVID-19 segmentation method based on the dense connectivity mechanism refers to the use of dense connectivity in the network for interconnection between any layers to achieve feature reuse for COVID-19 lesions segmentation. The use of dense connectivity in the model can reduce the interdependence between different layers and reduce the problem of difficult optimization due to gradient disappearance in the deep network. Zhao et al. [37] proposed a U-Net++ COVID-19 segmentation model, SCOAT-Net, to further reduce semantic gap and produce fine segmentation results by nesting dense jump paths connecting. Raj et al. [38] used two dense networks instead of traditional convolution in U-net networks to enhance global feature propagation, encourage feature reuse and accelerate information transfer to improve segmentation accuracy.

To sum up, there are some advantages in the segmentation methods of COVID-19 based on the attention mechanism, such as ignoring irrelevant feature information, selecting important feature information. However, the COVID-19 segmentation model with added attention mechanism usually has a complex model structure, and it is difficult to find a simple and lightweight segmentation model with an attention mechanism. The segmentation methods of COVID-19 based on multi-scale mechanism are beneficial to obtain the features of different size by combining multi-scale feature receptive fields, and thus improve the recognition ability of multi-scale target. However, the multi-scale mechanism may lose the continuity features by using different scales of receptive fields. The segmentation methods of COVID-19 based on residual connectivity mechanism are beneficial to speed-up

model gradient back propagation. Model training instability is prevented, and gradient disappearance avoided. However, it lacks the ability to explore segmentation feature extraction from the full scale. The segmentation methods of COVID-19 based on dense connectivity mechanism are beneficial to improve the efficiency of feature information transmission, which can better solve the problem of image detail loss and improve the segmentation performance of the network. However, it usually has a complex network structure and a lot of parameters in segmentation model.

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