

A Survey on Artificial Intelligence in Chest Imaging of COVID-19

Yun Chen¹, Gongfa Jiang^{2,4}, Yue Li^{2,4}, Yutao Tang^{2,4}, Yanfang Xu^{3,4}, Siqi Ding^{3,4}, Yanqi Xin^{2,4} and Yao Lu^{2,4,*}

Abstract

The coronavirus disease 2019 (COVID-19) has infected more than 9.3 million people and has caused over 0.47 million deaths worldwide as of June 24, 2020. Chest imaging techniques including computed tomography and X-ray scans are indispensable tools in COVID-19 diagnosis and its management. The strong infectiousness of this disease brings a huge burden for radiologists. In order to overcome the difficulty and improve accuracy of the diagnosis, artificial intelligence (AI)-based imaging analysis methods are explored. This survey focuses on the development of chest imaging analysis methods based on AI for COVID-19 in the past few months. Specially, we first recall imaging analysis methods of two typical viral pneumonias, which can provide a reference for studying the disease on chest images. We further describe the development of AI-assisted diagnosis and assessment for the disease, and find that AI techniques have great advantage in this application.

Keywords

Artificial intelligence, chest imaging analysis, COVID-19, deep learning, imaging findings.

¹School of Mathematics and Computational Science, Xiangtan University, Xiangtan, China

²School of Data and Computer Science, Sun Yat-sen University, Guangzhou, China

³School of Mathematics, Sun Yat-sen University, Guangzhou, China

⁴Guangdong Province Key Laboratory of Computational Science, Sun Yat-sen University, Guangzhou, China

Background

The coronavirus disease 2019 (COVID-19) is caused by the severe acute respiratory syndrome (SARS) coronavirus 2 (CoV-2), and has strong infectiousness, with over 9.3 million confirmed cases and about 0.47 million deaths worldwide as of June 24, 2020. In the clinical diagnosis of this disease, chest computed tomography (CT) and X-ray scans provide a supplement for real-time reverse-transcription polymerase chain reaction (RT-PCR) testing. As mentioned in [1], according to RT-PCR results, the sensitivity and accuracy of the disease infection on chest CT images are 97% and 68%, respectively. However, conventional diagnosis and analysis methods for CT/X-ray scans need a lot of manual labor and cost a large amount of time, leading to a huge burden to radiologists. To overcome these difficulties and improve the accuracy of diagnosis, artificial intelligence (AI) techniques based on deep learning have recently attracted extensive interests of researchers due to the superiority of AI in medical imaging analysis.

Currently, deep learning-based AI has been widely used in the medical imaging field as using it can achieve significantly better performance than traditional methods. The works in [2] and [3] provide a

comprehensive overview of deep learning methods in medical imaging analysis. For the localization and identification of thoracic diseases, Li et al. [4] applied the popular ResNet architecture introduced in [5] to build a computational model that can perform two such tasks simultaneously. With respect to the anatomical region of the chest, a technique based on a three-dimensional (3D) fully convolutional network (FCN) was proposed for the registration of lung CT inspiration–expiration image pairs in [6]. To study the categorization of focal/diffuse lung opacities in chest X-ray (CXR) images, Brestel et al. [7] presented a convolutional neural network (CNN)-based technique called RadBot-CXR, and claimed that their method achieved the level of radiologists for this task. Moreover, Ozturk et al. [8] applied a hand-crafted feature-based model for chest imaging analysis, where a stacked auto-encoder or principal component analysis (PCA) was applied to decrease the dimensions of the resulting feature vector, and the support vector machine (SVM) with a kernel was trained as the classifier.

AI-assisted chest imaging analysis methods have been studied to alleviate the pressure of radiologists and improve the efficiency of COVID-19 diagnosis. Dong et al. [9] investigated the role of imaging in

Correspondence to: Yao Lu
E-mail: luyao23@mail.sysu.edu.cn

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COVID-19 detection and its management. In that study, they reviewed different imaging modalities used for the detection, treatment, and follow-up of this disease, and described the development of AI-based quantitative analysis methods. Shi et al. [10] focused on the overview of AI techniques in chest imaging data acquisition, lung region/lesion segmentation, and diagnosis of COVID-19. Moreover, Mohamadou et al. [11] described mathematical modeling, AI, and the datasets involved in the study of COVID-19. With the pervasive spread of COVID-19, AI-assisted chest imaging analysis is urgently needed to extract the features of lung lesions and to develop an automatic diagnosis system for COVID-19. Hence, this survey focuses on reviewing AI-based imaging analysis methods for COVID-19 in the past few months, especially for CXR and chest CT images.

We have organized the survey as follows. In Section 2, we review the chest imaging analysis of two typical viral pneumonias, which provide a reference to analyze COVID-19. Section 3 is devoted to describing AI-assisted CXR imaging analysis methods of COVID-19. In Section 4, we give a description of AI-based chest CT imaging analysis methods for this disease. In Section 5, we conclude the paper and discuss future studies.

Imaging analysis for SARS and MERS

Chest imaging analysis of two typical viral pneumonias are briefly reviewed in this section, aiming at providing a reference to the study of COVID-19. These viral pneumonias include SARS and Middle East respiratory syndrome (MERS), which are global infectious pulmonary diseases caused by the coronavirus.

SARS was first found in China in November 2002, and it was followed by an outbreak in other areas and countries. The disease was caused by a coronavirus called SARS-CoV and infected hundreds of thousands of people. In particular, medical imaging analysis was an important approach in the retrospective study and prospective study of SARS [12–17]. Ooi et al. [12] evaluated chest imaging findings on CT scan for SARS in the acute and convalescent periods. In their study, they found that the main CT findings included ground-glass opacities (GGO) and consolidation, and there existed a temporal pattern of these findings in SARS. Zheng et al. [13] explored a computerized scheme to detect SARS in the early stage via CXR images. Chen et al. [14] studied image enhancement of the chest radiograph for improving the visualization of tissues and structures. In order to distinguish SARS-infected regions, Chen et al. [16] applied morphological operation and a graph-based optimization method to find the region of interest (ROI). The work in [17] also conducted a study on CXR images to recognize infected regions from normal regions by texture features and SVM. The results showed that the classification rate by the developed method was around 97%, which outperformed classification results by a multilevel PCA. Xie et al. [18] applied image mining techniques for the automatic detection of SARS. In this work, an active-shape model and its multiresolution version

were used for the segmentation of lesions. The work further applied a decision tree (DT), classification and regression tree, and a neural network method for the classifier. Their results showed that the classification rate by DT was better than that by the competing methods.

MERS, caused by the MERS-CoV, was first discovered in Saudi Arabia in September 2012 [19]. In order to further study MERS, its chest imaging findings were retrospectively analyzed in some publications. In particular, Das et al. [20] focused on the description of lung changes on serial CXR imaging findings of 55 cases with MERS and found that GGO was the most common finding. Das et al. [21] analyzed chest CT findings of 15 cases with MERS and identified features associated with survival. This work concluded that the 53% of patients had GGO, five patients had GGO and consolidation in combination, pleural effusion was found in 33% patients, four patients had interlobular thickening. Cha et al. [22] investigated a potential prognostic factor of fatal outcome for patients infected with MERS through the radiographic score, and demonstrated that a factor to predict fatal disease course is the corresponding score ≥ 10 on day 10 from viral exposure. The methods used in this work included receiver operating characteristic analysis and univariate/multivariate logistic regression (LR) analysis.

Imaging analysis of the aforementioned pneumonias investigated the common imaging findings on chest CT or CXR, which were also found in patients with COVID-19. As indicated in the literature [23–28], chest CT or CXR imaging findings for COVID-19 include GGO, consolidation, pleural changes, nodules, and other abnormalities. In particular, Ye et al. [26] listed in detail the occurrence rate of various CT imaging findings for COVID-19 from some recent literature. Figures of these findings are given in [25] and [26].

Furthermore, the aforementioned review can also provide a reference for the following study of COVID-19, such as the segmentation of lesions and the corresponding classification. These works in the aforementioned reviews demonstrated the availability of analysis methods in chest imaging, including the SVM, PCA, LR, and the neural network method. Recently, with the development of the AI technique, AI has become an important assistive tool in medical imaging analysis of COVID-19 in the past few months.

AI-assisted CXR imaging analysis for COVID-19

To assist radiologists to evaluate CXR imaging findings of COVID-19 and diagnose this disease, some machine learning- and/or deep learning-based automatic diagnosis and analysis methods were developed in the past few months (see **Table 1**). In particular, Ghoshal et al. [29] used drop-weights-based Bayesian CNN to estimate uncertainty in automatic prediction.

Recently, the developed automatic diagnosis methods of COVID-19 are mostly based on deep learning. However, training a deep learning model from scratch needs massive data, and there are no massive CXR images with COVID-19 pneumonia which are available for public. Hence, most

Table 1 AI-Assisted Diagnosis Methods for COVID-19 Based on CXR Images

Literature	Task	Method	Dataset	Result
Ozturk et al. [8]	Classification: Normal/ARDS/ pneumocystis pneumonia/ SARS/streptococcus/ COVID-19	Hand-crafted feature PCA SVM	2 normal 4 ARDS 2 pneumocystis pneumonia 11 SARS 6 streptococci 101 COVID-19	94.23% Acc. 91.88% Sen. 98.54% Spe. 96.73% Pre. 0.99 AUC
Abbas et al. [30]	Classification: Normal/SARS/COVID-19	Pretrained ResNet-18	80 normal 11 SARS 105 COVID-19	95.12% Acc. 97.91% Sen. 91.87% Spe. 93.36% Pre. 0.94 AUC
Apostolopoulos et al. [31]	Classification: Normal/bacterial pneumonia/COVID-19	Pretrained MobileNetV2	504 normal 700 bacterial pneumonia 224 COVID-19	92.85% Acc. 99.10% Sen. 97.09% Spe.
Farooq et al. [32]	Classification: Normal/bacterial pneumonia/non-COVID-19 pneumonia/COVID-19	Pretrained ResNet-50	1203 normal 931 bacterial pneumonia 660 non-COVID-19 pneumonia 68 COVID-19	96.23% Acc.
Lv et al. [33]	Classification: Normal/bacterial pneumonia/viral pneumonia (including COVID-19) Fine-grained classification: Non-COVID-19 pneumonia/ COVID-19	ResNet-50 U-Net DenseNet-169	1591 normal 2772 bacterial pneumonia 1493 viral pneumonia 316 non-COVID-19 pneumonia 125 COVID-19	85.62% Acc. 0.86 F1-score 97.14% Acc. 0.97 F1-score
Yeh et al. [34]	Classification: Normal/non-COVID-19 pneumonia/COVID-19	U-Net DenseNet-121	44993 normal 14777 non-COVID-19 pneumonia 167 COVID-19	85.26% Sen. 85.86% Spe. 0.88 AUC
Bassi and Attux [35]	Classification: Normal/non-COVID-19 pneumonia/COVID-19	CheXNet	1341 normal 1345 non-COVID-19 pneumonia 219 COVID-19	97.80% Recall 97.80% Pre. 0.98 F1-score
Rahimzadeh and Attar [36]	Classification: Normal/non-COVID-19 pneumonia/COVID-19	Xception ResNet- 50V2	8851 normal 6054 non-COVID-19 pneumonia 180 COVID-19	99.60% Acc.
Chowdhury et al. [37]	Classification: Normal/non-COVID-19 pneumonia/COVID-19	Pretrained deep CNN	190 COVID-19 1345 viral pneumonia 1341 normal	98.30% Acc. 96.70% Sen. 99.00% Spe.
Hemdan et al. [38]	Classification: Normal/COVID-19	VGG19 DenseNet	25 COVID-19 25 normal	0.89 F1-score
Basu et al. [39]	Classification: Normal/other disease/ pneumonia/COVID-19	Domain extension transfer learning	225 COVID-19 108948 normal and chest-related disease	95.30% ± 0.02 Acc.
Karim et al. [40]	Classification: Normal/non-COVID-19 pneumonia/COVID-19	DeepCOVID- Explainer	259 COVID-19 8614 non-COVID-19 pneumonia 8066 normal	89.61% PPV 83.00% Recall
Apostolopoulos et al. [41]	Classification	MobileNet V2	3905 images	99.18% Acc. 97.36% Sen. 99.42% Spe.
Li et al. [42]	Classification: Normal/non-COVID-19 pneumonia/COVID-19	Discriminative Cost-sensitive learning	239 COVID-19 1000 non-COVID-19 pneumonia 1000 normal	97.01% Acc. 97.09% Sen. 0.97 F1-score
Hall et al. [43]	Classification: Non-COVID-19 pneumonia/ COVID-19	ResNet-50	135 COVID-19 320 non-COVID-19 pneumonia	90.70% Acc. 0.99 AUC

Acc.: accuracy; AI: artificial intelligence; ARDS: acute respiratory distress syndrome; AUC: area under the curve; COVID-19: coronavirus disease 2019; CXR: chest X-ray; PCA: principal component analysis; PPV: positive predictive value; Pre.: precision; SARS: severe acute respiratory syndrome; Sen.: sensitivity; Spe.: specificity; SVM: support vector machine.

researches employed transfer learning to alleviate the data shortage problem through using models pretrained on the ImageNet dataset [31, 37, 44–46]. Specifically, Kana et al. [47] tuned a ResNet-50, pretrained on ImageNet, on a dataset sourced from three different repositories. The trained model was deployed with a web graphic user interface for inference for the medical research community. In order to deal with irregularities in the data distribution, Abbas et al. [30] used the decompose, transfer, and compose (DeTraC) method developed in their previous work to investigate class boundaries. In particular, they applied a class decomposition mechanism to partition each class into several potential sub-classes. Then, a ResNet-18 network pretrained on the ImageNet dataset was well tuned on the dataset with sub-classes. Here, they used data augmentation (DA) technique through flipping, rotation, and translation.

In passing, some studies further investigated the performance of various CNNs in CXR imaging analysis of COVID-19, for example [48–50]. Specifically, Punn and Agarwal [49] considered various state-of-the-art CNNs, including ResNet, Inception-v3, Inception ResNet-v2, DenseNet-169, and NASNetLarge. They also investigated class imbalanced learning approaches, including weighted class loss function and random oversampling of the minority class. Apostolopoulos et al. [31] investigated the performance of transfer learning by comparing some state-of-the-art CNN architectures, including VGG19, MobileNetV2, Inception, Xception, and Inception ResNet-v2. All the CNNs were pretrained with ImageNet, and the lower part of the networks were fixed during training. The last fully connected layer was replaced by the randomly initialized fully connected layer and trained. They found that MobileNetV2 achieved the highest overall performance with 92.85%, with a sensitivity of 99.10% and specificity of 97.09%.

Some deep learning methods without using transfer learning were developed to overcome the difficulty that the number of CXR images in the dataset may be deficient and unbalanced. Ozturk et al. [8] investigated the classification of COVID-19 images using shrunken features and a hand-crafted feature-based model. For chest images, this work extracted four kinds of features: the gray level co-occurrence matrix (GLCM), the local binary GLCM, the GL run length matrix, and the segmentation-based fractal texture analysis. The SVM with a kernel was trained as the classifier. To address the unbalanced problem, classical image augmentation (e.g., rotation and rescale) was applied to minority classes data. The synthetic minority oversampling technique (SMOTE) was also applied to oversample minority classes data. The results showed that using the developed model yielded an accuracy of 94.23%, sensitivity of 91.88%, specificity of 98.54%, precision of 96.73%, and AUC of 0.99. Kumar et al. [51] first trained a ResNet-152 to classify pneumonia-infected and normal patients. Then, the trained ResNet-152 was used to extract deep features from images of COVID-19-infected, pneumonia-infected, and normal patients. SMOTE was used to oversample minority classes data. Machine learning classifiers, such as random forest and XGBoost, were used for classifications on extracted features. Castiglioni et al. [52] developed an ensemble of 10 ResNet-50 trained on

bedside CXR images. The developed model was shown to outperform two experienced radiologists with no additional clinical information. Instead of using transfer learning and fine-tuning, Zhang et al. [53] used feature adversarial adaptation and proposed a novel classifier separation scheme to explicitly adapt knowledge learned from tasks with massive non-COVID-19 pneumonia data for COVID-19 classification.

The popular deep learning methods required heavy computational costs to train models due to the mass of the involved parameters. Luz et al. [54] investigated the EfficientNet family of models for COVID-19 diagnosis from CXR images due to the high computational cost of the popular deep learning methods. The results showed that this work brought about improvements with 93.90% accuracy, 96.80% sensitivity, and 100% positivity prediction. Compared to the baseline literature model, this study had about 30 times fewer parameters. Furthermore, parameters involved in this study are 28 and 5 times less than ResNet-50 and VGG16 architectures, respectively. Afshar et al. [55] used capsule network, which has much less parameters to train than CNNs, to handling small COVID-19 datasets. They also employed transfer learning on a large external dataset of X-ray images, which results in an increase in accuracy and specificity but a decrease in sensitivity.

Using data collected from different institutions has the risk that neural networks might learn patterns in CXR images which are correlated to the source of the data and not correlated to the presence of COVID-19. Maguolo and Nanni [56] showed that neural networks can learn to distinguish images of additional collected COVID-19 dataset from other datasets when lung regions are masked out. Researchers need to be careful and eliminate the data source factor when training and testing their neural networks.

Li et al. [57] developed COVID-MobileXpert for point-of-care COVID-19 screening by CXR, and demonstrated its strong potential in rapid deployment via extensive experiments. The COVID-MobileXpert is a mobile app based on the designed three-player knowledge transfer and distillation framework, consisting of a pretrained attending physician network, a fine-tuned resident fellow network, and a trained lightweight medical student network. Here, the first network was used to extract CXR imaging findings from large-scale lung disease CXR images; the second one was applied to learn the important findings for the recognition of this disease from viral pneumonia and/or normal cases via a small amount of COVID-19 cases; the third one performed on-device COVID-19 screening.

AI-based chest CT image analysis of COVID-19

Deep learning is the most common approach in computer-aided detection or diagnosis for medical imaging analysis. In COVID-19 diagnosis, some researchers developed different deep learning methods to assist radiologists in making more correct decisions and reducing their workload. These deep learning methods had similar flow charts, including

Table 2 Related Studies for AI-Based Chest CT Imaging Analysis Methods of COVID-19

Literature	Task	Method	Dataset	Result
Zhou et al. [58]	Segmentation: COVID-19 infection regions	U-Net with Focal Tversky Loss function	473 CT images	83.10% Dice 86.70% Sen. 99.30% Spe.
Qiu et al. [59]	Segmentation: COVID-19 infection regions	MiniSeg	100 CT images	97.42% Spe. 77.28% Dice
Xie et al. [60]	Segmentation: COVID-19 infection regions	Contextual two-stage U-Net	204 CT images	0.912±0.044 IOU 6.447±9.052 HD95
Yan et al. [61]	Segmentation: COVID-19 infection regions	COVID-SegNet	861 CT images	72.60% Dice 75.10% Sen.
Fan et al. [62]	Segmentation: COVID-19 infection regions	Semi-Inf-Net	100 CT images	73.90% Dice 72.50% Sen. 96.00% Spe.
	Segmentation: GGO	Semi-Inf-Net & FCN8s		64.60% Dice 72.00% Sen. 94.10% Spe.
	Segmentation: Consolidation	Semi-Inf-Net & Mutli-class U-Net		45.80% Dice 50.90% Sen. 96.70% Spe.
Shan et al. [63]	Segmentation: COVID-19 infection regions	VB-Net	549 CT images	91.6% ± 10.0% Dice
Chen et al. [64]	Segmentation: COVID-19 infection regions	U-Net ResNeXt	110 CT images	94.00% Dice 89.00% Acc.
Polsinelli et al. [65]	Classification: COVID-19/Non-COVID-19	Modified SqueezeNet	344 non-COVID-19 439 COVID-19	83.00% Acc. 85.00% Sen. 81.00% Spe.
		CNN		0.83 F1-score
Yousefzadeh et al. [66]	Classification: COVID-19/normal/non-COVID-19	CNN	654 normal 764 abnormal 706 COVID-19	0.99 AUC
Mobiny et al. [67]	Classification: COVID-19/non-COVID-19	Detail-Oriented Capsule Networks	349 COVID-19 397 non-COVID-19	0.96 AUC
Ozkaya et al. [68]	Classification: COVID-19/non-COVID-19	VGG-16	52 COVID-19	98.27% Acc.
		GoogLeNet	98 non-COVID-19	98.93% Sen.
		ResNet-50		97.60% Spe.
He et al. [69]	Classification: COVID-19/non-COVID-19	SVM		0.98 F1-score
		DenseNet-169 Self-Trans	349 COVID-19 397 non-COVID-19	0.85 F1-score 0.94 AUC

Acc.: accuracy; AI: artificial intelligence; AUC: area under the curve; CNN: convolutional neural network; COVID-19: coronavirus disease 2019; CT: computed tomography; GGO: ground-glass opacities; Sen.: sensitivity; Spe.: specificity; SVM: support vector machine.

segmentation, classification, and quantitative evaluation. Some related works were listed in **Table 2**.

AI-based lesion extraction in chest CT images

The key step of analyzing chest CT images is to extract lesions through COVID-19 lung infection segmentation including GGO and consolidation. AI techniques based on deep learning are developed to alleviate the task of radiologists and improve the accuracy of segmentation. Specifically, Rajinikanth et al. [70] proposed an automated image-processing scheme, which can extract the COVID-19 lesion from lung CT scan images. The pneumonia lesion was first enhanced by the firefly algorithm and the Shannon entropy-based multithreshold. Then, the proposed scheme applied the Markov random field segmentation for the extraction of COVID-19 lesions. This work was tested on 50 images of dimensions 512×512×1 and a mean segmentation accuracy of >92% was obtained. Rajinikanth et al. [71] further

proposed an image-assisted system which can extract the infected regions from CT images for COVID-19. The lung region was first extracted by a threshold filter, which can eliminate possible artifacts. Further, the system implemented the Harmony search optimization and Otsu’s thresholding to enhance the visibility of the infected regions, and used the watershed segmentation to extract them. Finally, the resulting ROI and the lung region were used to calculate the severity rate in patients with this disease.

Regular computer-aided detection systems need radiologists’ annotation as the ground truth to train the deep learning model. However, annotating all of the training data is time-consuming. Zheng et al. [72] presented a deep learning-based weakly supervised method to recognize COVID-19. The lung regions in each CT volumes were segmented by a pretrained U-Net. Then, the probability of COVID-19 was calculated by another 3D neural network for each volume. This process did not need the annotation of the lesions. It still obtained an AUC of 0.96. The detection speed was another benefit of this algorithm, where each patient took only 1.93 seconds on average in clinic application.

Song et al. [73] developed a diagnosis system of COVID-19 through a deep learning model, and had opened the system server online. Here, the resulting model could discriminate patients with COVID-19 and bacterial pneumonia. In particular, some main lesion features such as GGO could be provided to radiologists in the clinic when using this system. It can also help the radiologist read the CT images in less than 30 s.

AI-based detection and classification strategy of COVID-19

We review AI-based diagnosis for patients with COVID-19 in this section. Deep learning-based AI techniques were developed to recognize COVID-19 from other non-COVID-19 cases via chest CT images. In particular, Al-Karawi et al. [74] proposed the fast Fourier transformation (FFT)-Gabor scheme, which is a frequency domain algorithm, to test patients with COVID-19. This scheme first used an adaptive winner filter to improve image quality and selected a texture type. Then, the appropriate feature vector was extracted from the FFT spectrum, which was obtained by inversion. With the linear SVM as the classifier, this scheme achieved a classification average accuracy of 95.37% and sensitivity of 95.99%. Gozes et al. [75] proposed a system through two-dimensional (2D)/3D deep learning models to modify the popular AI models and combine them with clinical understanding. First, the U-Net architecture was trained on 6150 CT slices as a lung segmentation module. Then, the system used a ResNet-50-2D deep CNN architecture to detect coronavirus-related abnormalities. This system achieved a classification AUC of 0.99 with 94% sensitivity and 98% specificity. Hu et al. [76] proposed a detection and classification strategy for COVID-19 based on the weakly supervised deep learning. The input CT slices were first processed by a multiview U-Net to obtain the lung region. Then the segmented regions were input to the weakly supervised multiscale learning framework. Finally, the network architecture could get the suspicious lesions, which were classified as positive or negative. The developed model yielded high accuracy and AUC for the classification.

Gozes et al. [77] presented an algorithm based on deep learning for COVID-19 analysis in chest CT images. This included lung segmentation, classification, and fine grain localization. The lung segmentation and ROI selection adopted the U-Net architecture in which the encoder was pretrained with ImageNet. A ResNet-50-2D deep CNN architecture pretrained on ImageNet and DA techniques were employed in the process of classifying the lung ROIs into normal and abnormal. In addition, the paper proposed the corona score, which was calculated by adding up the activation diagram of positive test slices, to extract a quantitative metric for severity, where they employed only activation exceeding a predefined threshold of 0.6. The results of their method showed a high accuracy in classifying coronavirus versus non-coronavirus cases, and demonstrated that corona score corresponded to the clinical grade of the disease. Moreover, by unsupervised k-means feature clustering,

the prominent manifestations of the disease were divided into three different types: normal, focal, and diffuse.

Wu et al. [78] developed a novel diagnosis system to perform joint classification and segmentation (JCS) on CT images for COVID-19. This system first identified the suspected COVID-19 patients through a classification model and provided the diagnostic explanations via activation mapping techniques. Then, it employed the fine-grained image segmentation techniques to find out where the COVID-19 infection was located exactly. The classification model was based on the Res2Net network and the activation mapping located in the infected areas of COVID-19 patients as an explanation. The image mixing technique, which mixed the CT images with the corresponding patient-level annotations from different sources during training, was also utilized to provide more accurate locations of the lesion areas. In the part of segmentation, the model included an encoder and a decoder. The encoder was based on the VGG-16 backbone, without the last two fully connected layers. An enhanced feature module was added after the last layer to improve the representational power of the encoder. In the decoder, an attentive feature fusion approach was presented to aggregate the feature maps from different stages and to predict the side-output of each stage. The results implied that using the JCS system achieved high efficiency for COVID-19 in two such tasks. It obtained 78.3% Dice score on segmentation, superior to previous advanced segmentation methods, and classification results with a sensitivity of 95.0% and a specificity of 93.0%. Moreover, the JCS system took only 19.0 s per case, which was much faster than RT-PCR tests and CT scan analysis by experienced radiologists.

Wang et al. [79] presented a deep learning method for COVID-19 detection. This method used pretrained convolution layers to extract CT image findings. Then, more COVID-19-related data were enrolled to fine-tune this model. In the independent test set, this system successfully classified most of the COVID-19 cases from other pneumonia. When discriminating from viral pneumonia, the AUC was 0.86. In addition, the deep learning method divided the patients into “high-risk” and “low-risk” groups, which showed significant consistency with the hospital stay time of these patients.

Hu et al. [80] put forward a new AI method for the diagnosis of COVID-19 through a CNN with ShuffleNet V2 as the backbone network. In order to further enrich the sample size and enhance the robustness, the DA technique was also adopted. The experiments demonstrated that using the developed method can have a high AUC, sensitivity, specificity, and accuracy in classifying this disease from normal or other pneumonia (e.g., SARS) in the independent testing set. Moreover, the developed model was also robust even when some of the training samples were incorrectly labeled.

Other deep learning models were developed for COVID-19 diagnosis. Specifically, Jin et al. [81] proposed a deep learning-assisted detection model for COVID-19. The resulting model obtained the lung region through a segmentation network and achieved an accuracy of 94.98% in the classification of the independent external dataset. Moreover, the diagnosis time of this model was much shorter than that by radiologists. Jin et al. [82] proposed a 3D version lesion detection and diagnosis model through the 3D U-Net++

architecture. In the clinic, using this model can provide the reference location of the COVID-19 lesion to radiologists, and can obtain the corresponding classification results, which could reduce the workload of radiologists significantly. In the independent test set, this model attached 97% sensitivity and 92% specificity. As the authors mentioned, it had been used in 16 hospitals for clinical application. Li et al. [83] also used the deep learning method to detect COVID-19. This method, which is a classification model, can not only detect COVID-19 but also can recognize community-acquired pneumonia. Xu et al. [84] introduced a detection system of COVID-19 based on deep learning. The system can categorize COVID-19 and other viral pneumonia. The classification process used a location-attention scheme to give corresponding confidence scores. Finally, the infection type and the total confidence score for each patient was calculated by Bayesian function. The results showed that this system achieved an accuracy of 86.7%.

One of the benefits of deep learning methods is that it could be pretrained in similar data when the collected training data size is not large enough. The works in [72, 77], and [79] employed the pretrained networks (e.g., U-Net) to implement lung segmentation and lesion extraction. In [85], the authors modified the inception deep learning network and transferred it into COVID-19 diagnosis tasks. To evaluate the algorithm, both internal and external validation were implemented. The total accuracy was 89.5% with 88% specificity and 87% sensitivity for internal validation, but for external validation, the accuracy was 79.3% with 83% specificity and 67% sensitivity.

Some studies also investigated the performance of AI-based COVID-19 diagnosis, as compared to radiologists. Specifically, Ardakani et al. [86] compared the performance on distinguishing COVID-19 from non-COVID-19 cases for radiologists and some well-known CNNs. The CNNs include AlexNet, VGG-16, VGG-19, SqueezeNet, GoogLeNet, MobileNet-V2, ResNet-18, ResNet-50, ResNet-101, and Xception. The results showed that the ResNet-101 and Xception networks achieved the best performance in terms of AUC, while the radiologist got the worst performance. ResNet-101 had the highest sensitivity of COVID-19 diagnosis, as compared to the Xception network. Bai et al. [87] focused on the establishment and evaluation of an AI system used to distinguish COVID-19 and other pneumonias on chest CT images. Six radiologists without and with AI assistance blindly reviewed the study. They found that the developed system performed better than radiologists without AI assistance in testing the accuracy, sensitivity, and specificity. Compared to radiologists without AI assistance, the average accuracy, sensitivity, and specificity by radiologists with the assistance of the developed system increased 5%, 9%, and 3%, respectively. Chen et al. [88] applied the U-Net++ architecture to build an assisted system for COVID-19. This research conducted both a retrospective study and a prospective study. In the retrospective study, 20886 CT slices from 51 COVID-19 patients and 14469 CT slices from 55 normal cases were used to build and test the diagnosis model. In the prospective study, 27 patients were included, of which 16 of them were diagnosed as having COVID-19 by three experienced radiologists and the remaining 11 were normal. They

found that all of the 16 patients were correctly detected by the system, but two normal cases were detected as COVID-19 mistakenly. If the radiologists read CT images with the assistance of this model, the time of reading CT images was decreased by 65%, which is helpful in the clinic.

An AI technique based on deep learning was also used to explore the response of patients during treatment. Elghamrawy and Hassanien [89] put forward an AI-based model for diagnosing COVID-19 and predicting the response of patients to treatment. The resulting model had two main functions reflected in the two proposed modules, the diagnosis module based on CNNs for segmentation and the prediction module proposed for predicting the ability of the patient responding to treatment based on different factors. To verify the effectiveness of the developed model, this work compared the developed model with CorrCT, COVNet, DeConNet, and ReNet+ in three aspects of the overall precision, accuracy, and sensitivity. The results revealed the significant superiority of the developed model over the competing models in all these accounts and computing time.

AI-assisted quantitative evaluation of chest CT images

Quantitative evaluation is important to COVID-19 diagnosis and its management. AI-assisted quantitative evaluation helps radiologists to quickly make decisions and design the corresponding strategy for patients with COVID-19. Some indexes were used to quantitatively evaluate the severity of COVID-19 in studies. Li et al. [27] studied a visual quantitative index in CT and evaluated the performance of this index in the discrimination of severely critical patients. This quantitative index was calculated from five lobes of humans. In each lobe, a level was assessed by radiologists according to the acute lung inflammatory lesions in this lobe. Five discrete scores were the candidates for assessment: 0 (0%), 1 (1–25%), 2 (26–50%), 3 (51–75%), and 4 (76–100%), respectively. Then, the total severity score (TSS) was calculated by summing all of the lobe-assessed quantitative index. When TSS was used to discriminate the severely critical-type patients from all of the patients, it achieved an AUC of 0.92. Setting 7.5 as the threshold for TSS for severely critical patients, it attached a sensitivity of 82.6% and a specificity of 100%. As it was a subjective assessment by the radiologist, the consistency of two radiologists was also evaluated. The resulting intragroup correlation coefficient was 0.98, which is significantly consistent.

Shi et al. [90] established a deep learning method to quantitatively evaluate CT images. In particular, it was obvious that the pneumonia severity index (PSI) was a good index for classification of non-severe patients and severe cases. The developed method indicated the mass of infection and the percentage of infection, which were significantly higher in the severe group than the other groups. The AUC value in the test dataset was 0.89, which was higher than any univariate method.

Chaganti et al. [91] presented an automated quantification method for chest CT imaging findings of COVID-19 through the popular deep learning algorithms. In the segmentation

stage, they first employed multiscale deep reinforcement learning to detect anatomical landmarks. They further used a deep image-to-image network and DenseUNet to yield the segmentation. Due to the correlation between high-opacity abnormalities and severe disease, they introduced two combined metrics for evaluating the severity of COVID-19. They then calculated a Pearson correlation coefficient between each metric on the predicted masks and the corresponding ground truth masks, and obtained better results. The automated processing of computing the severity scores took 10 s/case, as compared to 30 min of manual annotations.

For the implementation of automatic quantification and prognosis assessment for COVID-19, Chassagnon et al. [92] proposed an end-to-end AI solution by the combination of automatic CT delineation of lung disease and data-driven identification of biomarkers. In this study, they investigated disease quantification, imaging biomarker discovery, and staging/prognosis for COVID-19. In order to quantify this disease and lung volume, they reported a segmentation tool based on deep learning. They further built an extended multicentric dataset for the assessment of the prognostic value of chest CT. For implementing the staging/prognosis, this work employed a hierarchical classification principle. Consequently, this study showed that the use of the prognosis/staging method can yield state-of-the-art results, and suggested that AI should be part of the triage process.

Conclusions and discussions

The world is facing a key health threat because of the outbreak of COVID-19. Intelligent medical imaging analysis is urgently needed to make full use of chest images in COVID-19 diagnosis and its management due to the important role of typical imaging findings in this disease. This paper reviewed AI-assisted chest imaging analysis methods for COVID-19 which provided accurate, fast, and safe imaging solutions. In particular, medical images from X-ray and CT scans are used to demonstrate that AI techniques based on deep learning have the ability in COVID-19 applications. In order to improve the performance of AI techniques, it is important to establish a database for public researches and to find a way to extract lesions accurately. Moreover, efficient deep learning models should be explored for COVID-19 applications.

It is important that multisource data can be applied to the diagnosis, monitoring, and prediction of COVID-19 as images from different imaging modalities can only show anatomical or functional information of patients with this disease. Here, the multisource data should include imaging findings, clinical symptoms, pathological features, blood tests, etc. In order to build analysis models purposefully and improve them, researchers can study the correlation among these datasets from different sources. This may help to maximize the value of AI in COVID-19 applications.

References

- [1] Ai T, Yang Z, Hou H, Zhan C, Chen C, et al. Correlation of chest CT and RT-PCR testing in coronavirus disease 2019 (COVID-19) in China: a report of 1014 cases. *Radiology* 2020;296:200642. [PMID: 32101510 DOI: 10.1148/radiol.2020200642]
- [2] Litjens G, Kooi T, Bejnordi B, Setio AA, Ciompi F, et al. A survey on deep learning in medical image analysis. *Med Image Anal* 2017;42:60-88. [PMID: 28778026 DOI: 10.1148/radiol.2020200642]
- [3] Altaf F, Islam S, Akhtar N, Janjua NK. Going deep in medical image analysis: concepts, methods, challenges and future directions. *IEEE Access* 2019;7:99540-72. [DOI: 10.1109/ACCESS.2019.2929365]
- [4] Li Z, Wang C, Han M, Xue Y, Wei W, et al. Thoracic disease identification and localization with limited supervision. 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) 2018. [DOI: 10.1109/CVPR.2018.00865]
- [5] He K, Zhang X, Ren S, Sun J. Deep residual learning for image recognition. In: *Proc IEEE Conf Comput Vis Pattern Recognit* 2016;770-8. [DOI: 10.1109/CVPR.2016.90]
- [6] Eppenhof K, Lafarge M, Moeskops P, Veta M, Pluim JPW. Deformable image registration using convolutional neural networks. *Proc SPIE* 2018;10574. [DOI: 10.1117/12.2292443]
- [7] Brestel C, Shadmi R, Tamir I, Cohen-Sfaty M, Elnekave E. Rad-Bot-CXR: classification of four clinical finding categories in chest X-ray using deep learning. In: *Proc 1st Conf Med Imag Deep Learn (MIDL)* 2018;1-9.
- [8] Ozturk S, Ozkaya U, Barstugan M. Classification of coronavirus images using Shrunken features. *MedRxiv* 2020. [DOI: 10.1101/2020.04.03.20048868]
- [9] Dong D, Tang Z, Wang S, Hui H, Gong L, et al. The role of imaging in the detection and management of COVID-19: a review. *IEEE Reviews in Biomedical Engineering* 2020. [PMID: 32356760 DOI: 10.1109/RBME.2020.2990959]
- [10] Shi F, Wang J, Shi J, Wu Z, Wang Q, et al. Review of artificial intelligence techniques in imaging data acquisition, segmentation and diagnosis for COVID-19. *IEEE Reviews in Biomedical Engineering* 2020. [PMID: 32305937 DOI: 10.1109/RBME.2020.2987975]
- [11] Mohamadou Y, Halidou A, Kapen P. A review of mathematical modeling, artificial intelligence and datasets used in the study, prediction and management of COVID-19. *Appl Intell* 2020;1-13. [DOI: 10.1007/s10489-020-01770-9]
- [12] Ooi G, Khong P, Muller N, Yiu WC, Zhou LJ, et al. Severe acute respiratory syndrome: temporal lung changes at thin-section CT in 30 patients. *Radiology* 2004;230:836-44. [PMID: 14990845 DOI: 10.1148/radiol.2303030853]
- [13] Zheng Z, Lan R, Lv G. A computerized scheme of SARS detection in early stage based on chest image of digital radiograph. *Proc SPIE* 5370, *Medical Imaging 2004: Image Processing* 2004;5370:904-14. [DOI: 10.1117/12.535232]
- [14] Chen S, Hou H, Zeng Y, Xiaomin X. Study of automatic enhancement for chest radiograph. *J Digit Imaging* 2006;19:371-5. [PMID: 16752044 DOI: 10.1007/s10278-006-0623-7]
- [15] Gong T, Pei L, Gao S, Han F, Zhao S, et al. Visual netlogo-based simulation of anti-SARS immune system and low-to-high resolution reconstruction of sequence medical CT images anti-SARS CT. 2015 International Workshop on Artificial Immune Systems (AIS), Taormina 2015;1-8. [DOI: 10.1109/AISW.2015.7469238]
- [16] Chen S, Cao L, Liu L, Tang X. Automatic segmentation of lung fields from radiographic images of SARS patients using a new graph cuts algorithm. 18th International Conference on Pattern Recognition (ICPR'06), Hong Kong 2006;1:271-4. [DOI: 10.1109/ICPR.2006.304]
- [17] Tang X, Tao D, Antonio G. Texture classification of SARS infected region in radiographic image. 2004 International Conference on Image Processing, Singapore 2004;5:2941-4. [DOI: 10.1109/ICIP.2004.1421729]
- [18] Xie X, Gong Y, Wan S, Xi L. Computer aided detection of SARS based on radiographs data mining. 2005 IEEE Engineering in Medicine and Biology 27th Annual Conference, Shanghai 2005;7:7459-62. [PMID: 17282006 DOI: 10.1109/IEMBS.2005.1616237]

[19] Zaki A, Van Boheemen S, Bestebroer T, Osterhaus AD, Fouchier RA. Isolation of a novel coronavirus from a man with pneumonia in Saudi Arabia. *N Eng J Med* 2012;367:1814-20. [PMID: 23075143 DOI: 10.1056/NEJMoa1211721]

[20] Das K, Lee E, Jawder S, Enani MA, Singh R, et al. Acute Middle East respiratory syndrome coronavirus: temporal lung changes observed on the chest radiographs of 55 patients. *Am J Roentgenol* 2015;205:W267-74. [PMID: 26102309 DOI: 10.2214/AJR.15.14445]

[21] Das K, Lee E, Enani M, Al Jawder SE, Singh R, et al. CT correlation with outcomes in 15 patients with acute Middle East respiratory syndrome coronavirus. *Am J Roentgenol* 2015;204:736-42. [PMID: 25615627 DOI: 10.2214/AJR.14.13671]

[22] Cha M, Chung M, Kim K, Lee KS, Kim TJ, et al. Clinical implication of radiographic scores in acute Middle East respiratory syndrome coronavirus pneumonia: report from a single tertiary-referral center of South Korea. *Eur J Radiol* 2018;107:196-202. [PMID: 30292266 DOI: 10.1016/j.ejrad.2018.09.008]

[23] Wang H, Lan H, Fong A, Leung ST, Chin T, et al. Frequency and distribution of chest radiographic findings in COVID-19 positive patients. *Radiology* 2020;296:E72-8. [PMID: 32216717 DOI: 10.1148/radiol.2020201160]

[24] Guan W, Ni Z, Hu Y, Liang W-H, Ou C-Q, et al. Clinical characteristics of coronavirus disease 2019 in China. *N Eng J Med* 2020;382:1708-20. [PMID: 32109013 DOI: 10.1056/NEJMoa2002032]

[25] Bernheim A, Mei X, Huang M, Yang Y, Fayad ZA, et al. Chest CT findings in coronavirus disease-19 (COVID-19): relationship to duration of infection. *Radiology* 2020;295:200463. [PMID: 32077789 DOI: 10.1148/radiol.202000463]

[26] Ye Z, Zhang Y, Wang Y, Huang Z, Song B. Chest CT manifestations of new coronavirus disease 2019 (COVID-19): a pictorial review. *Eur Radiol* 2020;30:4381-9. [PMID: 32193638 DOI: 10.1007/s00330-020-06801-0]

[27] Li K, Fang Y, Li W, Pan C, Qin P, et al. CT image visual quantitative evaluation and clinical classification of coronavirus disease (COVID-19). *Eur Radiol* 2020;30:4407-16. [PMID: 32215691 DOI: 10.1007/s00330-020-06817-6]

[28] Chung M, Bernheim A, Mei X, Zhang N, Huang M, et al. CT imaging features of 2019 novel coronavirus (2019-nCoV). *Radiology* 2020;295:202-7. [PMID: 32017661 DOI: 10.1148/radiol.202000230]

[29] Ghoshal B, Tucker A. Estimating uncertainty and interpretability in deep learning for coronavirus (COVID-19) detection. *ArXiv*. 2020; arXiv:2003.10769.

[30] Abbas A, Abdelsamea M, Gaber M. Classification of COVID-19 in chest X-ray images using DeTraC deep convolutional neural network. *ArXiv*. 2020; arXiv:2003.13815.

[31] Apostolopoulos I, Mpesiana T. Covid-19: automatic detection from X-Ray images utilizing transfer learning with convolutional neural networks. *Phys Eng Sci Med* 2020;43:635-40. [PMID: 32524445 DOI: 10.1007/s13246-020-00865-4]

[32] Farooq M, Hafeez A. COVID-ResNet: a deep learning framework for screening of COVID19 from radiographs. *ArXiv*. 2020; arXiv:2003.14395.

[33] Lv D, Qi W, Li Y, Sun L, Wang Y. A cascade network for detecting COVID-19 using chest X-rays. *ArXiv*. 2020; arXiv:2005.01468.

[34] Yeh C, Cheng H, Wei A, Chen H-M, Kuo P-C, et al. A cascaded learning strategy for robust COVID-19 pneumonia chest X-Ray screening. *ArXiv*. 2020; arXiv:2004.12786.

[35] Bassi P, Attux R. A deep convolutional neural network for COVID-19 detection using chest X-Rays. *ArXiv*. 2020; arXiv:2005.01578.

[36] Rahimzadeh M, Attar A. A modified deep convolutional neural network for detecting COVID-19 and pneumonia from chest X-ray images based on the concatenation of Xception and ResNet50V2. *Informatics in Medicine Unlocked* 2020;19:100360. [PMID: 32501424 DOI: 10.1016/j.imu.2020.100360]

[37] Chowdhury M, Rahman T, Khandakar A, Mazhar R, Kadir MA, et al. Can AI help in screening viral and COVID-19 pneumonia? *ArXiv*. 2020; arXiv:2003.13145. [DOI: 10.1109/ACCESS.2020.3010287]

[38] Hemdan E, Shouman M, Karar M. COVIDX-Net: a framework of deep learning classifiers to diagnose COVID-19 in X-ray images. *ArXiv*. 2020; arXiv:2003.11055.

[39] Basu S, Mitra S, Saha N. Deep learning for screening COVID-19 using chest X-ray images. *ArXiv*. 2020; arXiv:2004.10507.

[40] Karim M, Döhmen T, Rebholz-Schuhmann D. DeepCOVIDExplainer: explainable COVID-19 prediction based on chest X-ray images. *ArXiv*. 2020; arXiv:2004.04582.

[41] Apostolopoulos I, Azaouridis S, Mpesiana T. Extracting possibly representative COVID-19 biomarkers from X-ray images with deep learning approach and image data related to pulmonary diseases. *J Med Biol Eng*. 2020;40:462-9. [PMID: 32412551 DOI: 10.1007/s40846-020-00529-4]

[42] Li T, Han Z, Wei B, Zheng Y, Hong Y, et al. Robust screening of COVID-19 from chest X-ray via discriminative cost-sensitive learning. *ArXiv*. 2020; arXiv:2004.12592.

[43] Hall L, Paul R, Goldgof D, Goldgof GM. Finding Covid-19 from chest X-rays using deep learning on a small dataset. *ArXiv*. 2020; arXiv:2004.02060.

[44] Narin A, Kaya C, Pamuk Z. Automatic detection of coronavirus disease (COVID-19) using X-ray images and deep convolutional neural networks. *ArXiv*. 2020; arXiv:2003.10849.

[45] Zhang J, Xie Y, Li Y, Shen C, Xia Y. COVID-19 screening on chest X-ray images using deep learning based anomaly detection. *ArXiv*. 2020; arXiv:2003.12338.

[46] Wang L, Wong A. COVID-Net: a tailored deep convolutional neural network design for detection of COVID-19 cases from chest radiography images. *ArXiv*. 2020; arXiv:2003.09871.

[47] Kana E, Kana M, Kana AF, Kenfack R. A web-based diagnostic tool for COVID-19 using machine learning on chest radiographs (CXR). *MedRxiv* 2020;1-17. [DOI: 10.1101/2020.04.21.20063263]

[48] Minaee S, Kafieh R, Sonka M. Deep-COVID: predicting COVID-19 from chest X-ray images using deep transfer learning. *Med Image Anal* 2020;65:101794. [PMID: 32781377 DOI: 10.1016/j.media.2020.101794]

[49] Punn N, Agarwal S. Automated diagnosis of COVID-19 with limited posteroanterior chest X-ray images using fine-tuned deep neural networks. *ArXiv*. 2020; arXiv:2004.11676.

[50] Rajaraman S, Siegelman J, Alderson P. Iteratively pruned deep learning ensembles for COVID-19 detection in chest X-rays. *IEEE Access* 2020;8:115041-50. [PMID: 32742893 DOI: 10.1109/access.2020.3003810]

[51] Kumar R, Arora R, Bansal V, Sahayasheela VJ, Buckchash H, et al. Accurate prediction of COVID-19 using chest X-ray images through deep feature learning model with SMOTE and machine learning classifiers. *MedRxiv* 2020;1-10. [DOI: 10.1101/2020.04.13.20063461]

[52] Castiglioni I, Ippolito D, Interlenghi M, Salvatore C, Schiaffino S, et al. Artificial intelligence applied on chest X-ray can aid in the diagnosis of COVID-19 infection: a first experience from Lombardy, Italy. *MedRxiv* 2020. [DOI: 10.1101/2020.04.08.20040907]

[53] Zhang Y, Niu S, Qiu Z, Wei Y, Zhao P, et al. COVID-DA: deep domain adaptation from typical pneumonia to COVID-19. *ArXiv*. 2020; arXiv:2005.01577.

[54] Luz E, Silva P, Silva R. Towards an effective and efficient deep learning model for COVID-19 patterns detection in X-ray images. *ArXiv*. 2020; arXiv:2004.05717.

[55] Afshar P, Heidarian S, Naderkhani F, Oikonomou A, Plataniotis KN, et al. COVID-CAPS: a capsule network-based framework for identification of COVID-19 cases from X-ray image. *ArXiv*. 2020; arXiv:2004.02696.

[56] Maguolo G, Nanni L. A critic evaluation of methods for COVID-19 automatic detection from X-ray images. *ArXiv*. 2020; arXiv:2004.12823.

[57] Li X, Li C, Zhu D. COVID-MobileXpert: on-device COVID-19 screening using snapshots of chest X-ray. *ArXiv*. 2020; arXiv:2004.03042.

[58] Zhou T, Canu S, Ruan S. An automatic COVID-19 CT segmentation network using spatial and channel attention mechanism. *ArXiv*. 2020; arXiv:2004.06673.

[59] Qiu Y, Liu Y, Xu J. MiniSeg: an extremely minimum network for efficient COVID-19 segmentation. *ArXiv*. 2020; arXiv:2004.09750.

[60] Xie W, Jacobs C, Charbonnier J, van Ginneken B. Contextual two-stage U-Nets for robust pulmonary lobe segmentation in CT Scans of COVID-19 and COPD patients. *ArXiv*. 2020; arXiv:2004.07443.

[61] Yan Q, Wang B, Gong D, Luo C, Zhao W, et al. COVID-19 chest CT image segmentation—A deep convolutional neural network solution. *ArXiv*. 2020; arXiv:2004.10987.

- [62] Fan D, Zhou T, Ji G, Zhou Y, Chen G, et al. Inf-Net: automatic COVID-19 lung infection segmentation from CT scans. *IEEE Trans Med Imaging* 2020;39:2626–37. [PMID: 32730213 DOI: 10.1109/TMI.2020.2996645]
- [63] Shan F, Gao Y, Wang J, Shi W, Shi N, et al. Lung infection quantification of COVID-19 in CT images with deep learning. *ArXiv*. 2020; arXiv:2003.04655.
- [64] Chen X, Yao L, Zhang Y. Residual attention U-net for automated multi-class segmentation of COVID-19 chest CT images. *ArXiv*. 2020; arXiv:2004.05645.
- [65] Polsinelli M, Cinque L, Placidi G. A light CNN for detecting COVID-19 from CT scans of the chest. *ArXiv*. 2020; arXiv:2004.12837.
- [66] Yousefzadeh M, Esfahanian P, Movahed S, Gorgin S, Lashgari R, et al. Ai-corona: radiologist-assistant deep learning framework for COVID-19 diagnosis in chest CT scans. *MedRxiv* 2020;1-14. [DOI: 10.1101/2020.05.04.20082081]
- [67] Mobiny A, Cicalese P, Zare S, Yuan P, Abavisani M, et al. Radiologist-level COVID-19 detection using CT scans with detail-oriented capsule networks. *ArXiv*. 2020; arXiv:2004.07407.
- [68] Ozkaya U, Ozturk S, Barstugan M. Coronavirus (COVID-19) classification using deep features fusion and ranking technique. *ArXiv*. 2020; arXiv:2004.03698.
- [69] He X, Yang X, Zhang S, Zhao J, Zhang Y, et al. Sample-efficient deep learning for COVID-19 diagnosis based on CT scans. *MdeRxiv* 2020;1-10. [DOI: 10.1101/2020.04.13.20063941]
- [70] Rajinikanth V, Kadry S, Thanaraj K, Kamalanand K, Seo S. Firefly-algorithm supported scheme to detect COVID-19 lesion in lung CT scan images using Shannon Entropy and Markov-Random-Field. *ArXiv*. 2020; arXiv:2004.09239.
- [71] Rajinikanth V, Dey N, Raj A. Harmony-search and Otsu based system for coronavirus disease (COVID-19) detection using lung CT scan images. *ArXiv*. 2020; arXiv:2004.03431.
- [72] Zheng C, Deng X, Fu Q, Zhou, Q, Feng, J, et al. Deep learning-based detection for COVID-19 from chest CT using weak label. *MedRxiv* 2020;1-13. [DOI: 10.1101/2020.03.12.20027185]
- [73] Song Y, Zheng S, Li L, Zhang X, Zhang X, et al. Deep learning enables accurate diagnosis of novel coronavirus (COVID-19) with CT images. *MedRxiv* 2020;1-10. [DOI: 10.1101/2020.02.23.20026930]
- [74] Al-Karawi D, Al-Zaidi S, Polus N, Jassim S. Machine learning analysis of chest CT scan images as a complementary digital test of coronavirus (COVID-19) patients. *MedRxiv* 2020;1-8. [DOI: 10.1101/2020.04.13.20063479]
- [75] Gozes O, Frid-Adar M, Greenspan H, Browning PD, Zhang H, et al. Rapid AI development cycle for the coronavirus (COVID-19) pandemic: initial results for automated detection & patient monitoring using deep learning CT image analysis. *ArXiv*. 2020; arXiv:2003.05037.
- [76] Hu S, Gao Y, Niu Z, Jiang Y, Li L, et al. Weakly supervised deep learning for COVID-19 infection detection and classification from CT images. *ArXiv*. 2020; arXiv:2004.06689.
- [77] Gozes O, Frid-Adar M, Sagie N, Zhang H, Ji W, et al. Coronavirus detection and analysis on chest CT with deep learning. *ArXiv*. 2020; arXiv:2004.02640.
- [78] Wu Y, Gao S, Mei J, Xu J, Fan DP, et al. JCS: an explainable COVID-19 diagnosis system by joint classification and segmentation. *ArXiv*. 2020; arXiv:2004.07054.
- [79] Wang S, Zha Y, Li W, Wu Q, Li X, et al. A fully automatic deep learning system for COVID-19 diagnostic and prognostic analysis. *Eur Respir J* 2020;56:2000775. [PMID: 32444412 DOI: 10.1183/13993003.00775-2020]
- [80] Hu R, Ruan G, Xiang S, Huang M, Liang Q, et al. Automated diagnosis of COVID-19 using deep learning and data augmentation on chest CT. *MedRxiv* 2020;1-11. [DOI: 10.1101/2020.04.24.20078998]
- [81] Jin C, Chen W, Cao Y, Xu Z, Zhang X, et al. Development and evaluation of an AI system for COVID-19 diagnosis. *MedRxiv* 2020;1-23. [DOI: 10.1101/2020.03.20.20039834]
- [82] Jin S, Wang B, Xu H, Luo C, Wei L, et al. AI-assisted CT imaging analysis for COVID-19 screening: building and deploying a medical AI system in four weeks. *MedRxiv* 2020;1-22. [DOI: 10.1101/2020.03.19.20039354]
- [83] Li L, Qin L, Xu Z, Yin Y, Wang X, et al. Using artificial intelligence to detect covid-19 and community-acquired pneumonia based on pulmonary CT: evaluation of the diagnostic accuracy. *Radiology* 2020;295:E65-71. [PMID: 32191588 DOI: 10.1148/radiol.20200905]
- [84] Xu X, Jiang X, Ma C, Du P, Li X, et al. Deep learning system to screen coronavirus disease 2019 pneumonia. *ArXiv*. 2020; arXiv:2002.09334.
- [85] Wang S, Kang B, Ma J, Ma J, Zeng X, et al. A deep learning algorithm using CT images to screen for corona virus disease (COVID-19). *MedRxiv* 2020;1-27. [DOI: 10.1101/2020.02.14.20023028]
- [86] Ardakani A, Kanafi A, Acharya U, Khadem N, Mohammadi A. Application of deep learning technique to manage COVID-19 in routine clinical practice using CT images: results of 10 convolutional neural networks. *Comput Biol Med* 2020;121:103795. [PMID: 32568676 DOI: 10.1016/j.compbiomed.2020.103795]
- [87] Bai H, Wang R, Xiong Z, Hsieh B, Chang K, et al. AI augmentation of radiologist performance in distinguishing COVID-19 from pneumonia of other etiology on chest CT. *Radiology* 2020;296:E156-165. [PMID: 32339081 DOI: 10.1148/radiol.2020201491]
- [88] Chen J, Wu L, Zhang J, Zhang L, Gong D, et al. Deep learning-based model for detecting 2019 novel coronavirus pneumonia on high-resolution computed tomography: a prospective study. *MedRxiv* 2020;1-9. [DOI: 10.1101/2020.02.25.20021568]
- [89] ELGhamrawy S, Hassanien A. Diagnosis and prediction model for COVID-19 patient's response to treatment based on convolutional neural network and whale optimization algorithm using CT images. *MedRxiv* 2020;1-23. [DOI: 10.1101/2020.04.16.20063990]
- [90] Shi W, Peng X, Liu T, Cheng Z, Lu H, et al. Deep learning-based quantitative computed tomography model in predicting the severity of COVID-19: a retrospective study in 196 patients. *SSRN* 2020; 1-32. [DOI: 10.2139/ssrn.3546089]
- [91] Chaganti S, Balachandran A, Chabin G, Cohen S, Flohr T, et al. Quantification of tomographic patterns associated with COVID-19 from chest CT. *ArXiv*. 2020; arXiv:2004.01279. [PMID: 32550252]
- [92] Chassagnon G, Vakalopoulou M, Battistella E, Christodoulidis S, Hoang-Thi TN, et al. AI-driven CT-based quantification, staging and short-term outcome prediction of covid-19 pneumonia. *MedRxiv* 2020;1-16. [DOI: 10.1101/2020.04.17.20069187]