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CHEST IMAGING

REVIEW

A review on the use of artificial intelligence for medical imaging of the lungs of patients with coronavirus disease 2019

Rintaro Ito
Shingo Iwano
Shinji Naganawa

ABSTRACT

The results of research on the use of artificial intelligence (AI) for medical imaging of the lungs of patients with coronavirus disease 2019 (COVID-19) has been published in various forms. In this study, we reviewed the AI for diagnostic imaging of COVID-19 pneumonia. PubMed, arXiv, medRxiv, and Google scholar were used to search for AI studies. There were 15 studies of COVID-19 that used AI for medical imaging. Of these, 11 studies used AI for computed tomography (CT) and 4 used AI for chest radiography. Eight studies presented independent test data, 5 used disclosed data, and 4 disclosed the AI source codes. The number of datasets ranged from 106 to 5941, with sensitivities ranging from 0.67–1.00 and specificities ranging from 0.81–1.00 for prediction of COVID-19 pneumonia. Four studies with independent test datasets showed a breakdown of the data ratio and reported prediction of COVID-19 pneumonia with sensitivity, specificity, and area under the curve (AUC). These 4 studies showed very high sensitivity, specificity, and AUC, in the range of 0.9–0.98, 0.91–0.96, and 0.96–0.99, respectively.

A new type of pneumonia was reported from Wuhan, China in December 2019. The cause was first reported as the novel coronavirus of 2019; the disease was subsequently called coronavirus disease 2019 (COVID-19), and the virus was formally named severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) (1). This viral infection is spreading rapidly (1–4), and was declared by the World Health Organization (WHO) to be a pandemic in March 2020. Reverse transcriptase polymerase chain reaction (RT-PCR) is used to diagnose infection with the virus, which causes pneumonia (5). The usefulness of computed tomography (CT) and chest radiography for the diagnosis of COVID-19 associated pneumonia has been reported (6, 7). The ability of radiologists to diagnose COVID-19 pneumonia from chest CT evaluations has been reported to be very high (8). The characteristic CT finding of COVID-19 pneumonia is pulmonary ground-glass opacities in a peripheral distribution (9–11).

There has been recent progress in integrating artificial intelligence (AI) with computer-aided design (CAD) software for diagnostic imaging (12–17). Progress has occurred as a result of the convolutional neural network (CNN) published by Hinton et al. (18) in 2011, and the Neocognitron network published by Fukushima (19), which is rapidly improving its ability to identify images.

A wide range of developments have occurred in the field of medical imaging, which have improved the various tasks involved in the detection of diagnostic features. AI is now being developed rapidly around the world to aid in combating the rapid expansion of COVID-19. An early summary of the discriminatory ability of AI is needed at this time, 3 months after the recognition of this disease. The assessment of the use of AI in the diagnostic imaging of patients with COVID-19 could be a test case for the type of AI selected in the early stages of future emerging diseases, and also for providing information on the size of the dataset to be used and on the appropriate use of AI. In this paper, we review the diagnostic performance of the recently published AI on radiological imaging of COVID-19 pneumonia.

From the Department of Innovative Biomedical Visualization (R.I. ✉ *rintaro-ito@med.nagoya-u.ac.jp*), Nagoya University Graduate School of Medicine, Showa-ku, Nagoya, Japan; Department of Radiology (S.I., S.N.), Nagoya University Graduate School of Medicine, Showa-ku, Nagoya, Japan.

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Methods

The PubMed, arXiv, medRxiv and Google Scholar databases were searched up to March 27, 2020, to extract articles on imaging and AI used for COVID-19. The search terms "COVID-19" and "SARS-CoV-2" were combined with "artificial intelligence", "deep learning" and "machine learning". Among these articles, only those that involved studies of AI for computed tomography (CT) and chest radiography were selected. Although many of the articles were preprints, we included those that we thought satisfied the purposes of this review. We extracted the number of datasets from these studies, with respect to those that included COVID-19, the number of test sets and the proportion of cases, sensitivity, specificity, and area under the curve (AUC). We also investigated the publication of the datasets and the source codes.

Results

A total of 27 papers were extracted from PubMed, 98 from Google Scholar, 48 from arXiv, and 3 from medRxiv. Duplications were removed, and only papers related to imaging were extracted. There were 4 peer-reviewed papers and 9 non-peer-reviewed papers from arXiv, and 7 non-peer-reviewed papers from medRxiv. Fourteen papers were about the creation of AI software and the accuracy of AI for predicting COVID-19 (Table); 3 papers reported on the modification of existing AI software to COVID-19; one AI software program predicted the severity of COVID-19, and two AI software programs measured the spread and progression of the pneumonia lesions.

Peer-reviewed papers

We identified one peer-reviewed study describing development and validation of a novel AI program, and two case presentations and one letter that used existing AI programs and software.

Li et al. (20) developed a CT-based AI program for detecting patients with COVID-19 pneumonia. The sensitivity, specificity, and AUC for the diagnosis of COVID-19 pneumonia were 90%, 96%, and 0.96, respectively. The network was trained by data that included 400 patients with COVID-19, 1396 patients with community-acquired pneumonia, and 1173 patients with normal CT or no pneumonia. The network was evaluated by testing it with data from 68 patients with COVID-19, 155 patients with community-acquired pneumonia, and 130 patients with normal CT or no pneumonia. The patients with COVID-19 were diagnosed by RT-PCR. The study dataset was large and the accuracy was high. The dataset was not disclosed, but the source code was, and could be illustrated by gradient-weighted class activation mapping (Grad-CAM). Grad-CAM could provide quick judgments against the results of AI. The paper by Li et al. (20) was published on March 19, 2020, and is one of the very early and effective studies. The actual accuracy of detecting patients with COVID-19 pneumonia by the developed AI should be assessed in further follow-up studies.

Li et al. (21) adapted an AI-based software program (InferVISION) for the CT assessment of 2 patients with COVID-19. AI allowed them to suspect pneumonia and to calculate the percentage of ground-glass opacities. They reported that AI was clinically useful. They used an existing software, not one that was developed for predicting COVID-19. Hurt et al. (22) evaluated conventional chest radiographic images of 10 patients with COVID-19. The evaluation was performed by UNet, trained on their existing dataset. The extraction of the lung regions affected by pneumonia was well done, indicating versatility in existing AI. Cao et al. (23) used UNet to calculate the volume of pulmonary ground-glass opacities in 10 COVID-19 patients. Their AI approach may be useful in evaluating images over time.

Studies published on arXiv

Many of the AI studies on arXiv were published after mid-March, 2020, because of the release of the datasets (24–26). There were 6 studies related to the use of AI on CT images. The earliest publication was that of Xu et al. (27) on February 21, 2020. They developed an AI program based on the CT scans from patients with COVID-19, which showed a sensitivity and specificity for diagnosis of COVID-19 pneumonia of 86.7% and 81.3%, respectively. They trained the network using data from 189 patients with COVID-19, 194 patients with influenza-associated pneumonia, and 145 patients with normal CT findings; and evaluated the network with test data from 30 patients with COVID-19, 30 patients with influenza pneumonia, and 30 patients with normal CT findings. Shan et al. (28) used V-net and V-bet-based networks to generate an AI program that assessed the extent of lesion spread, with a Dice similarity coefficient of 91.6%±10% and a percentage of infection (POI) estimation error of 0.3%. COVID-19 pneumonia is characterized by bilateral peripheral ground-glass opacities, which change over time (6, 7). Ground-glass opacities might be useful for assessing the morbidity of patients diagnosed with COVID-19. Barstugan et al. (29) developed Support Vector Machine (SVM) for CT scans of patients with COVID-19 using 150 open data set (26), including 53 COVID-19 cases. The CT data were annotated on a slice-by-slice basis, and the training assessment might have included data from the same cases. Although the evaluation was limited because the training assessment did not consist of independent test data, the results showed extremely high sensitivity (93%) and specificity (100%) in classification of COVID-19 pneumonia. Additional studies might allow calculations of the actual accuracy of this SVM in detecting COVID-19. Shi et al. (30) used data from 1658 patients with COVID-19 and 1027 patients with community-acquired pneumonia to generate an AI. Lung fields and ground-glass opacities segmentation was performed, and classification was performed by a random forest model. In detection of COVID-19 pneumonia, five-fold cross validation was used to obtain a sensitivity and specificity of 90% and 83%, respectively. El-Din Hemdan et al. (31) used data from conventional chest radiographic images of 25 cases with normal lungs and 25 cases of COVID-19 to compare an AI program with multiple known network structures. VGG19 and Densely Connected Convolutional Networks (DenseNet) (32, 33) showed the best results of classification with COVID-19 in their review. Twenty cases with normal radiographic images and 20 with COVID-19 findings were used as training data and 5 normal/5 COVID-19 cases were used as test data. The AI pro-

Main points

- A medical imaging AI program applied to COVID-19 patients provides high accuracy in the diagnosis of COVID-19 pneumonia during the early stages of its emergence.
- Studies with independent datasets and detailed AI evaluations showed excellent predictive accuracy.
- The actual accuracy of AI in detecting patients with COVID-19 pneumonia should be assessed in further follow-up studies.

Table. AI for COVID-19 pneumonia classification

Author	Modality	Dataset	2D/3D	All data	All Covid-19	Train (all/Covid-19)	Test (all/Covid-19)	Cross validation	Independent test	Sensitivity	Specificity	AUC	Dataset	Code URL
Li et al. (20)	CT	COVID-19/CAP/normal	3D	3322	468	2969/400	353/68		Yes	0.90	0.96	0.96	Not open	https://github.com/bkong999/COVNet
Shi et al. (30)	CT	COVID-19/CAP	3D	2685	1658			5	No	0.91	0.83	0.94	Not open	
Wang et al. (44)	CT	COVID-19/pneumonia/normal	3D	1266	924	709/560	226/102, 161/92		Yes	0.80/0.79	0.76/0.81	N/A	Not open	
Xu et al. (27)	CT	COVID-19/fluA/normal	3D	618	219	528/189	90/30		Yes	0.87	0.81	N/A	Not open	
Jin et al. (41)	CT	COVID-19/normal	2D	595	379	296/196	299/183		Yes	0.94	0.95	0.97	Not open	https://github.com/ChenWWWeixiang/diagnosis_covid19
Zheng et al. (45)	CT	COVID-19/other	3D	540	313	499 / N/A	131/ N/A		Yes	0.90	0.91	0.97	Not open	https://github.com/sydney0zq/covid-19-detection
Song et al. (42)	CT	COVID-19/normal/bacterial	2D	275	88	N/A	N/A		No	0.93	0.96	0.99	Not open	
Wang et al. (43)	CT	COVID-19/normal	2D	259	195	N/A	N/A		No	0.67	0.83	N/A	Not open	
Gozes et al. (34)	CT	COVID-19/normal	2D/3D	206	106	50/50	56/51, 56/49		Yes	0.98	0.92	0.99	Not open	
Barstugan et al. (29)	CT	COVID-19/other	2D	150	53			10	No	0.93	1.00	N/A	Open	
Chen et al. (40)	CT	COVID-19/other	2D	106	51	64/40	42/11		Yes	1.00	0.93	N/A	Not open	
Ghoshal et al. (35)	CXR	COVID-19/normal	2D	N/A	70			10	No	N/A	N/A	N/A	Open	
Wang et al. (36)	CXR	COVID-19/normal/bacterial/viral	2D	5941	68	N/A	N/A		N/A	1.00	N/A	N/A	Open	https://github.com/lindawangg/COVID-Net
Apostolopoulos et al. (37)	CXR	COVID-19/CAP/normal	2D	1427	224			10	No	0.99	0.97	N/A	Open	
El-Din Hemdan et al. (31)	CXR	COVID-19/normal	3D	50	25	40/20	10/5		Yes	1.00	0.80	N/A	Open	

Additional datasets for pretrain is not included in this Table.
2D/3D, two-dimensional/three-dimensional; All data, a number of all dataset for the study; All COVID-19, a number of COVID-19 dataset for the study; Train (all/COVID-19), a number of all dataset for train and A number of COVID-19 dataset for train; Test (all/COVID-19), a number of all dataset for test and A number of COVID-19 dataset for test; AUC, area under the curve; CT, computed tomography; CXR, chest radiography; CAP, community acquired pneumonia; fluA, influenza pneumonia; N/A, not applicable.

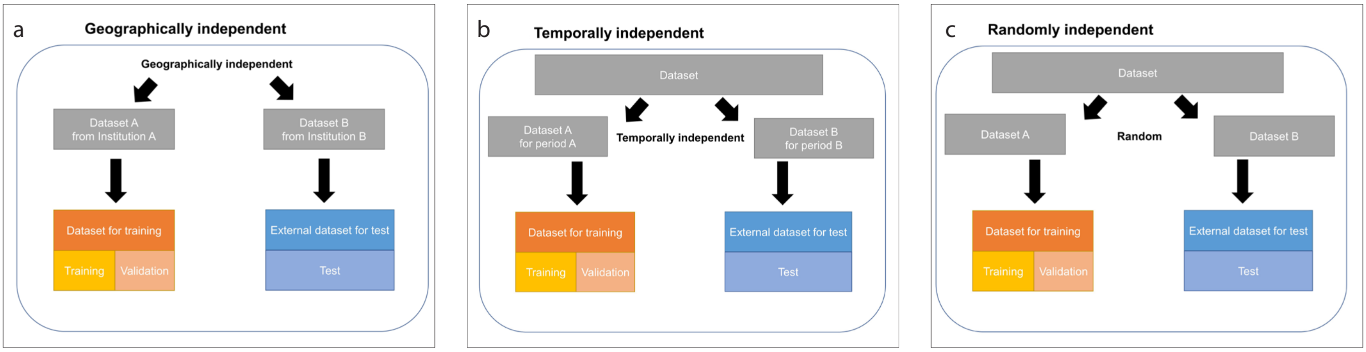

Figure 1. a–c. How to split independent test dataset. The external test dataset is geographically **(a)**, temporally **(b)**, or randomly **(c)** independent of training and validation dataset.

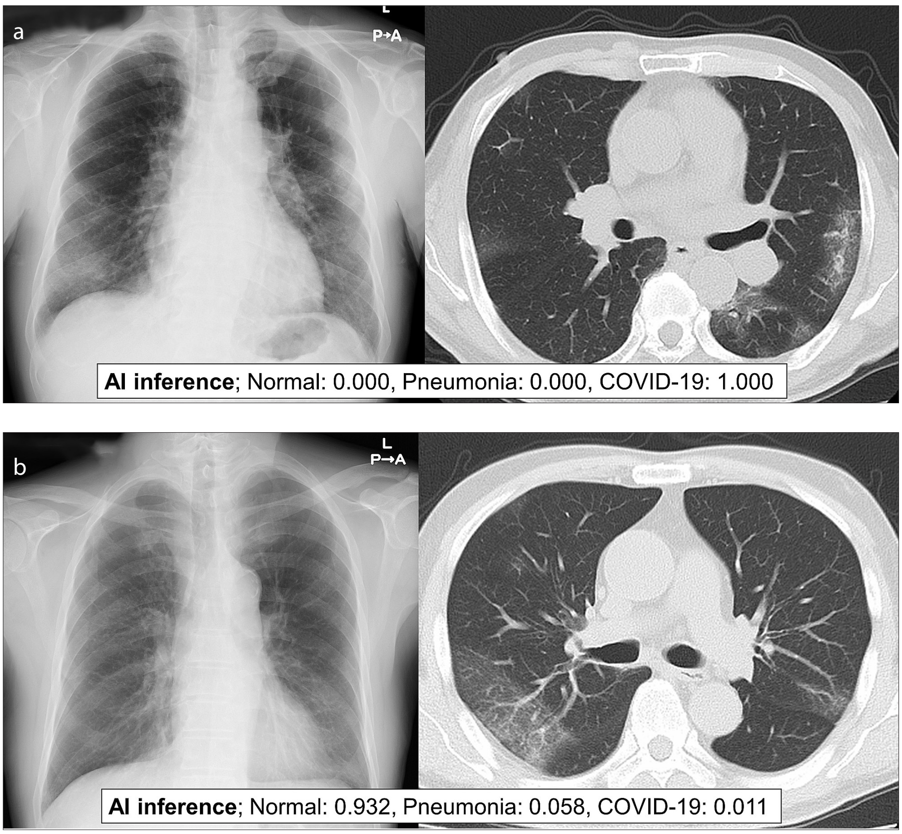

Figure 2. a, b. Panel **(a)** shows AI analysis example based on chest radiography and chest CT of a 73-year-old woman with positive RT-PCR result for SARS-Cov-2. We used pretrained COVIDNet model (COVIDNet-CXR large; model-8485.data-00000-of-00001) (36). AI predicted the patient's chest radiography as COVID-19. Panel **(b)** shows another example of AI analysis based on chest radiography and chest CT of a 73-year-old man with positive RT-PCR result for SARS-Cov-2. We used pretrained COVIDNet model (COVIDNet-CXR large; model-8485.data-00000-of-00001) (36). In this case, AI failed to predict the chest radiography as COVID-19.

gram for classification of COVID-19 pneumonia obtained a sensitivity and specificity of 100% and 80%, respectively. Gozes et al. (34) used an AI program applied to chest CT and showed excellent classification ability for COVID-19, with a sensitivity, specificity, and AUC of 98.2%, 92.2%, and 0.996, respectively. Their program could identify COVID-19 pneumonia with high accuracy. In addition, they built an AI system that can be used from detection to follow-up, with graphical representation and quantification. A dataset of 206 cases including 106 patients with COVID-19 was used.

There were 3 studies of conventional chest radiographs published on ArXiv. Ghoshal et al. (35) examined 70 cases from the COVID-19 dataset published in the Bayesian Convolutional Neural Networks. A dataset of normal cases was added, but the number of cases is unknown. They used 10-fold cross-validation and calculated accuracies in the range of 85.7–92.9 in detection of COVID-19 pneumonia. The sensitivity and specificity have not been calculated. Wang et al. (36) conducted a study aimed at creating an AI program to detect COVID-19 pneumonia. They used a published database containing data on 68 COVID-19 cases, 1203 normal cases, 931 cases of bacterial pneumonia, and 660 cases of non-COVID-19 viral pneumonia. The sensitivity was 100%. No mention was made of the breakdown or specificity of the training and test data. The dataset is still being expanded, and further enhancement of the database is anticipated. We used this AI program for our own case of COVID-19 pneumonia (Fig. 2). Apostolopoulos et al. (37) examined an AI program using data from 224 published COVID-19 cases, 700 pneumonia cases, and 504 normal cases. The network and database are available for validation and refinement worldwide. They compared known networks that used transfer learning, evaluated by 10-fold cross validation and found that Mobile Net (38) showed the best results, obtaining a sensitivity and specificity of 99.1% and 97.1%, respectively, in detection of COVID-19.

Studies published on medRxiv

All studies for AI of COVID-19 in medRxiv used chest CT. Bai et al. (39) used logistic regression analysis and deep-learning–based methods to estimate the severity factors in 133 patients with COVID-19. Chen et al. (40) performed a prospective study of 27 cases. The dataset for training and testing contained 51 patients with COVID-19 and 55 patients with other diseases. The sensitivity and specificity for identification of COVID-19 pneumonia were 100% and 93.5% respectively, showing good analytical results; the prospective study had a sensitivity and specificity of 100% and 81.8% respectively, showing lower specificity and higher sensitivity than the results of the test. Jin et al. (41) reported that the AI was trained on data from 296 COVID-19 positive patients and 100 COVID-19 negative patients, and the AI program was evaluated on 183 COVID-19 positive patients and 113 COVID-19 negative patients. The sensitivity and specificity for detection of COVID-19 pneumonia were 94% and 96%, respectively. They published the source code for the AI, which can be verified. A study by Song et al. (42) used 88 COVID-19 positive patients, 86 healthy cases, and 100 patients with bacterial pneumonia to examine an AI program. They divided the CT scans into each slice and dividing the cases into training/validation/test sets at corresponding ratios of 0.6/0.1/0.3. Cross validation was not mentioned, and the same cases could have been included in the training/test sets. Wang et al. (43) reported that they used data from 454 cases, including a COVID-19 dataset of 195 cases, to generate an AI program. The sensitivity and specificity in classification of COVID-19 pneumonia were 67% and 83%, respectively. Wang et al. (44) generated an AI program using a training dataset which included CT scans of 924 cases with COVID-19 and 342 cases of other pneumonia. For test, they used two datasets: one dataset included 102 cases with COVID-19 and 124 cases of other pneumonia; the other dataset included 92 cases with COVID-19 and 69 cases of other pneumonia. The sensitivity and specificity for diagnosis of COVID-19 pneumonia were 79% and 81%, respectively. The ability of outcome prediction was also evaluated. Their system could predict high/low risk for outcome of COVID-19 pneumonia. Zheng et al. (45) developed an AI program using 540 patients, including 313 patients with COVID-19 pneumonia. The AI program was evaluated by dividing 540 patients into training/validation datasets and a test dataset according to different time periods. The percentages of the data sets are not disclosed for each, but they are independent test sets. They calculated sensitivity as 90%, specificity 91%, and AUC 0.97.

Discussion

As COVID-19 is spreading worldwide and a large number of patients require testing, RT-PCR testing should be the best criterion, but in populations with increasing risk of infection, an AI program might be useful as an aid to diagnosis.

In our review, 5 studies used open dataset, and 4 studies disclosed source code. The datasets ranged from small to large. There are ethical issues that need to be addressed when it comes to releasing datasets, and research is being accelerated by open datasets that have been cleared of these problems. It is expected that the research will be further accelerated with published source codes and open datasets.

In almost all studies of CT (20, 27, 30, 41–45), preprocessing and extraction of affected lung fields were performed. The methods for preprocessing and extraction varied from the classical use of CT values to the use of U-Net (46). U-Net is very useful because it prevents inaccurate identification of areas other than the lung field.

CT was used in 11 studies (20, 27, 29, 30, 34, 40–45), and a conventional chest radiography was used in 4 studies (31, 35–37). There were 8 studies that had independent test data (20, 27, 31, 34, 40, 41, 44, 45) (Fig. 1). There were 4 datasets that had independent datasets with a breakdown of the data and reports on the sensitivity, specificity, and AUC (20, 34, 41, 45). These studies showed very high sensitivity, specificity, and AUC of 0.9–0.98, 0.91–0.96, and 0.96–0.99, respectively.

AI can evaluate the findings that radiologists can recognize. In addition, the AI can evaluate findings that radiologists cannot recognize. For example, the risk of developing serious complications of COVID-19 and the susceptibility for developing COVID-19 could also be assessed if an appropriate database were established. If these AIs can be developed and used to detect high-risk people before they are infected with COVID-19, social distancing can be used more effectively to protect them.

Conclusion

This review summarizes the currently published imaging and AI research for COVID-19. Those studies with independent datasets and detailed AI evaluations showed excellent predictive accuracy.

Conflict of interest disclosure

The authors declared no conflicts of interest.

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