Imaging Modalities for COVID-19 Diagnosis

Subjects: Computer Science, Artificial Intelligence

Contributor: Xue Han , Zuojin Hu , Shuihua Wang , Yudong Zhang

The spread and severity of COVID-19 are alarming. The economy and life of countries worldwide have been greatly affected. The rapid and accurate diagnosis of COVID-19 directly affects the spread of the virus and the degree of harm. The X-ray and computed tomography (CT) can image the lungs of patients with COVID-19. Lung imaging can reveal the niduses' spatial location and the infection's extent.

COVID-19 diagnosis deep learning convolutional neural networks CT images

1. Introduction

WHO declared COVID-19 as a global pandemic in March 2020. The COVID-19 pandemic has affected thousands of people. It has affected people's ordinary lives and the global economy. COVID-19 can cause respiratory, gastrointestinal, and neurological syndromes [1]. Cough, fever, and other respiratory issues are the most common symptoms [2].

Rapid COVID-19 diagnosis is essential during the pandemic. Currently, the commonly used diagnostic methods include the molecular assay, chest computed tomography (CT) scan combined with the evaluation of clinical symptoms [3], artificial intelligence (AI) methods [4], potential electrochemical (EC) biosensors [5], surface plasmon resonance (SPR)-based biosensors [6], field-effect transistor (FET)-based biosensors [7], etc. As a frequently employed auxiliary detection technology, CT images can show the changes in the lung caused by virus infection [8]. Compared with CT images, X-ray images are more accessible to obtain. It is also an important means of medical detection.

The most common diagnostic measure for COVID-19 is through reverse transcription-polymerase chain reaction (RT-PCR) assays of nasopharyngeal swabs [9]. However, the high false negative rate of RT-PCR [10] may affect the timely treatment of infected patients. The X-ray and CT can image the lungs of patients with COVID-19. Lung imaging can reveal the niduses' spatial location and the infection's extent. CT images have a fast turnaround and excellent sensitivity [11]. They can visualize the degree of infection in the lung. Based on the significant features of COVID-19 on X-ray or CT images, many researchers have used artificial intelligence and computer vision to classify X-ray or CT images. These images were classified into two categories: those without COVID-19 and those infected with COVID-19. Other researchers divided the images into healthy, infected with COVID-19, and infected with pneumonia. Some algorithms can detect the extent of infection based on the features of X-ray or CT images. This research is meant to help doctors diagnose COVID-19 accurately and quickly.

Artificial intelligence is widely used in medical [12][13][14]. Its accuracy rates and prediction are high [15]. AI can be applied to multiple phases, such as prediction, diagnosis, virus detection, response, prevention, and recovery, to accelerate research [16][17]. During the COVID-19 epidemic, AI recognized chest X-rays or CT images. Features in X-ray or CT images are extracted for COVID-19 diagnosis by segmenting regions of interest and capturing fine structures. One of the important subfields of AI is machine learning (ML) [18]. It is already widely applied to medical images [19][20][21]. Deep learning (DL) is a promising technology in machine learning [22]. Deep learning has multiple hidden layers for learning and can perform classification or detection tasks well [23][24]. The role of deep learning in image recognition is vital [19][25][26][27]. The convolutional neural network (CNN) is a kind of deep network. It is popular in computer vision applications. CNN has been successfully applied to biological image segmentation [28], traffic sign recognition [29][30][31], face recognition [32][33], and other fields. Later studies added rectified linear units, dropout, data augmentation, and other techniques to CNN. This decreased the error rate of deep learning for image classification tasks to less than 3% in 2016 [34] and exceeded human performance.

2. Imaging Modalities for COVID-19 Diagnosis

Computed tomography (CT), published in 1972 [35], has become a widely used tool for diagnostic imaging. CT is a cross-sectional scan of a certain part of the human body one by one. Its advantages include clear images and fast scanning. CT is widely used to detect a variety of diseases. X-rays penetrate a person's body and take an X-ray image. X-ray images are also an important basis for diagnosing diseases.

2.1. Chest Computed Tomography

CT takes images from different angles. One shot was taken for each rotation angle. Using a large number of projection images taken from different angles, it can be back-calculated a fault plane image by a mathematical algorithm. This is computed tomography. Many scholars have studied the features of COVID-19 on CT images. In the study of patients in Rome and Italy [8], ground glass opacity (GGO) was found in 100% of confirmed patients on CT images. Ground-glass opacity (GGO) means that the density will be slightly increased on high-resolution CT images, and the bronchovascular will still be visible. This sign is often the manifestation of early lung disease. Timely detection and diagnosis of GGO are important for clinical management. Multilobe and posterior lung involvement was present in 93% of patients. Bilateral pneumonia occurred in 91% of patients. Cellina et al. [36] concluded that GGO was more common bilaterally in the peripheral lung areas under the pleura on CT images of COVID-19. During the disease, the number of consolidations increases, forming fibrotic stripes. Consolidation refers to accumulating fluids, fibrin, and cellular components in the alveolar airspaces. It reduces alveolar air content and increases parenchymal density. Wang et al. [37] found that CT manifestations of mild/common-type infection were multifocal lesions, GGO, involving multiple segments or lobes. CT manifestations of heavy/critical-type infection show consolidation of multiple lesions and interlobular septal thickening. In the paper [38], Bernheim et al. mentioned that the CT image features of COVID-19 are consolidative pulmonary opacities and bilateral and peripheral ground glass. The longer the onset of symptoms, the more findings on CT images. These findings include bilateral and peripheral disease, consolidation, linear opacities, greater total lung involvement, the "reverse halo" sign, and a "crazy-paving" pattern. In Guan's study [2], 56.4% of the COVID-19 subjects showed GGO.

2.2. Chest X-ray

X-rays are emitted from one end, passed through the body, and picked up by a detector at the other end. What is received is a two-dimensional image. So X-ray imaging is fast and cheap. Chest X-ray images of patients diagnosed with COVID-19 show air space consolidation and the bilateral distribution of peripheral hazy lung opacities [39]. When COVID-19 is suspected, the preferred imaging modality for the chest is the X-ray [40]. The radiation dose of chest X-rays is lower than CT, and chest X-rays are cheaper [41]. Because portable chest X-ray is easy to carry and clean, chest X-ray can reduce the risk of COVID-19 transmission during testing [42]. According to Oh [43], although the sensitivity of chest X-ray results is not high (69%) [39], chest X-rays can be used to determine the sequence of treatment for patients infected with COVID-19. Diagnosing chest X-rays can alleviate the saturated healthcare system during the COVID-19 pandemic.

References

1. Manigandan, S.; Wu, M.-T.; Ponnusamy, V.K.; Raghavendra, V.B.; Pugazhendhi, A.; Brindhadevi, K. A systematic review on recent trends in transmission, diagnosis, prevention and imaging features of COVID-19. Process Biochem. 2020, 98, 233–240.
2. Guan, W.-J.; Ni, Z.-Y.; Hu, Y.; Liang, W.-H.; Ou, C.-Q.; He, J.-X.; Liu, L.; Shan, H.; Lei, C.-L.; Hui, D.S. Clinical characteristics of coronavirus disease 2019 in China. New Engl. J. Med. 2020, 382, 1708–1720.
3. Nour, M.; Cömert, Z.; Polat, K. A novel medical diagnosis model for COVID-19 infection detection based on deep features and Bayesian optimization. Appl. Soft Comput. 2020, 97, 106580.
4. Cui, F.; Zhou, H.S. Diagnostic methods and potential portable biosensors for coronavirus disease 2019. Biosens. Bioelectron. 2020, 165, 112349.
5. Zhu, X.; Wang, X.; Han, L.; Chen, T.; Wang, L.; Li, H.; Li, S.; He, L.; Fu, X.; Chen, S. Multiplex reverse transcription loop-mediated isothermal amplification combined with nanoparticle-based lateral flow biosensor for the diagnosis of COVID-19. Biosens. Bioelectron. 2020, 166, 112437.
6. Qiu, G.; Gai, Z.; Tao, Y.; Schmitt, J.; Kullak-Ublick, G.A.; Wang, J. Dual-functional plasmonic photothermal biosensors for highly accurate severe acute respiratory syndrome coronavirus 2 detection. ACS Nano 2020, 14, 5268–5277.
7. Sengupta, J.; Hussain, C.M. Graphene-based field-effect transistor biosensors for the rapid detection and analysis of viruses: A perspective in view of COVID-19. Carbon Trends 2021, 2, 100011.
8. Caruso, D.; Zerunian, M.; Polici, M.; Pucciarelli, F.; Polidori, T.; Rucci, C.; Guido, G.; Bracci, B.; De Dominicis, C.; Laghi, A. Chest CT features of COVID-19 in Rome, Italy. Radiology 2020, 296,

201237.

9. Xie, X.; Zhong, Z.; Zhao, W.; Zheng, C.; Wang, F.; Liu, J. Chest CT for typical 2019-nCoV pneumonia: Relationship to negative RT-PCR testing. Radiology 2020, 296, 200343.
10. Chan, J.F.-W.; Yuan, S.; Kok, K.-H.; To, K.K.-W.; Chu, H.; Yang, J.; Xing, F.; Liu, J.; Yip, C.C.-Y.; Poon, R.W.-S. A familial cluster of pneumonia associated with the 2019 novel coronavirus indicating person-to-person transmission: A study of a family cluster. Lancet 2020, 395, 514–523.
11. Hussain, L.; Nguyen, T.; Li, H.; Abbasi, A.A.; Lone, K.J.; Zhao, Z.; Zaib, M.; Chen, A.; Duong, T.Q. Machine-learning classification of texture features of portable chest X-ray accurately classifies COVID-19 lung infection. BioMedical Eng. OnLine 2020, 19, 88.
12. Górriz, J.M.; Ramírez, J.; Ortíz, A.; Martínez-Murcia, F.J.; Segovia, F.; Suckling, J.; Leming, M.; Zhang, Y.-D.; Álvarez-Sánchez, J.R.; Bologna, G. Artificial intelligence within the interplay between natural and artificial computation: Advances in data science, trends and applications. Neurocomputing 2020, 410, 237–270.
13. Soomro, T.A.; Zheng, L.; Afifi, A.J.; Ali, A.; Yin, M.; Gao, J. Artificial intelligence (AI) for medical imaging to combat coronavirus disease (COVID-19): A detailed review with direction for future research. Artif. Intell. Rev. 2022, 55, 1409–1439.
14. Yang, L.; Li, Z.; Ma, S.; Yang, X. Artificial intelligence image recognition based on 5G deep learning edge algorithm of Digestive endoscopy on medical construction. Alex. Eng. J. 2022, 61, 1852–1863.
15. Gorriz, J.M.; Ramirez, J.; Suckling, J.; Martínez-Murcia, F.J.; Illán, I.; Segovia, F.; Ortiz, A.; Salas-Gonzalez, D.; Castillo-Barnes, D.; Puntonet, C.G. A semi-supervised learning approach for model selection based on class-hypothesis testing. Expert Syst. Appl. 2017, 90, 40–49.
16. Pesapane, F.; Codari, M.; Sardanelli, F. Artificial intelligence in medical imaging: Threat or opportunity? Radiologists again at the forefront of innovation in medicine. Eur. Radiol. Exp. 2018, 2, 1–10.
17. Górriz, J.M.; Ramírez, J.; Segovia, F.; Martínez, F.J.; Lai, M.-C.; Lombardo, M.V.; Baron-Cohen, S.; Consortium, M.A.; Suckling, J. A machine learning approach to reveal the neurophenotypes of autisms. Int. J. Neural Syst. 2019, 29, 1850058.
18. Satapathy, S.; Loganathan, D.; Kondaveeti, H.K.; Rath, R. Performance analysis of machine learning algorithms on automated sleep staging feature sets. CAAI Trans. Intell. Technol. 2021, 6, 155–174.
19. Lee, J.-G.; Jun, S.; Cho, Y.-W.; Lee, H.; Kim, G.B.; Seo, J.B.; Kim, N. Deep learning in medical imaging: General overview. Korean J. Radiol. 2017, 18, 570–584.

20. Varoquaux, G.; Cheplygina, V. Machine learning for medical imaging: Methodological failures and recommendations for the future. NPJ Digit. Med. 2022, 5, 1–8.

21. Elyan, E.; Vuttipittayamongkol, P.; Johnston, P.; Martin, K.; McPherson, K.; Moreno-García, C.F.; Jayne, C.; Sarker, M.K. Computer vision and machine learning for medical image analysis: Recent advances, challenges, and way forward. Artif. Intell. Surg. 2022, 2, 24–25.

22. Gasparin, A.; Lukovic, S.; Alippi, C. Deep learning for time series forecasting: The electric load case. CAAI Trans. Intell. Technol. 2022, 7, 1–25.

23. LeCun, Y.; Bengio, Y.; Hinton, G. Deep learning. Nature 2015, 521, 436–444.

24. Mukherjee, S.; Sadhukhan, B.; Sarkar, N.; Roy, D.; De, S. Stock market prediction using deep learning algorithms. CAAI Trans. Intell. Technol. 2021. early view.

25. Serte, S.; Serener, A.; Al-Turjman, F. Deep learning in medical imaging: A brief review. Trans. Emerg. Telecommun. Technol. 2022, 33, e4080.

26. Tsuneki, M. Deep learning models in medical image analysis. J. Oral Biosci. 2022, 64, 312–320.

27. Liu, X.; Yang, L.; Chen, J.; Yu, S.; Li, K. Region-to-boundary deep learning model with multi-scale feature fusion for medical image segmentation. Biomed. Signal Process. Control 2022, 71, 103165.

28. Ning, F.; Delhomme, D.; LeCun, Y.; Piano, F.; Bottou, L.; Barbano, P.E. Toward automatic phenotyping of developing embryos from videos. IEEE Trans. Image Process. 2005, 14, 1360–1371.

29. CireAan, D.; Meier, U.; Masci, J.; Schmidhuber, J. Multi-column deep neural network for traffic sign classification. Neural Netw. 2012, 32, 333–338.

30. Abdel-Salam, R.; Mostafa, R.; Abdel-Gawad, A.H. RIECNN: Real-time image enhanced CNN for traffic sign recognition. Neural Comput. Appl. 2022, 34, 6085–6096.

31. Karthika, R.; Parameswaran, L. A novel convolutional neural network based architecture for object detection and recognition with an application to traffic sign recognition from road scenes. Pattern Recognit. Image Anal. 2022, 32, 351–362.

32. Chen, L.-C.; Papandreou, G.; Kokkinos, I.; Murphy, K.; Yuille, A.L. Semantic image segmentation with deep convolutional nets and fully connected crfs. arXiv 2014, arXiv:1412.7062.

33. Du, H.; Shi, H.; Zeng, D.; Zhang, X.-P.; Mei, T. The elements of end-to-end deep face recognition: A survey of recent advances. ACM Comput. Surv. (CSUR) 2022, 54, 1–42.

34. Large Scale Visual Recognition Challenge 2016 (ILSVRC2016) Results. Available online: http://image-net.org/challenges/LSVRC/2016/ (accessed on 1 April 2022).

35. Hounsfield, G.N. Computerized transverse axial scanning (tomography): Part 1. Description of system. Br. J. Radiol. 1973, 46, 1016–1022.

36. Cellina, M.; Orsi, M.; Valenti Pittino, C.; Toluian, T.; Oliva, G. Chest computed tomography findings of COVID-19 pneumonia: Pictorial essay with literature review. Jpn. J. Radiol. 2020, 38, 1012–1019.

37. Wang, J.; Xu, Z.; Feng, R.; An, Y.; Ao, W.; Gao, Y.; Wang, X.; Xie, Z. CT characteristics of patients infected with 2019 novel coronavirus: Association with clinical type. Clin. Radiol. 2020, 75, 408–414.

38. Bernheim, A.; Mei, X.; Huang, M.; Yang, Y.; Fayad, Z.A.; Zhang, N.; Diao, K.; Lin, B.; Zhu, X.; Li, K. Chest CT findings in coronavirus disease-19 (COVID-19): Relationship to duration of infection. Radiology 2020, 295, 200463.

39. Wong, H.Y.F.; Lam, H.Y.S.; Fong, A.H.-T.; Leung, S.T.; Chin, T.W.-Y.; Lo, C.S.Y.; Lui, M.M.-S.; Lee, J.C.Y.; Chiu, K.W.-H.; Chung, T.W.-H. Frequency and distribution of chest radiographic findings in patients positive for COVID-19. Radiology 2020, 296, E72–E78.

40. Jokerst, C.; Chung, J.H.; Ackman, J.B.; Carter, B.; Colletti, P.M.; Crabtree, T.D.; de Groot, P.M.; Iannettoni, M.D.; Maldonado, F.; McComb, B.L. ACR Appropriateness Criteria® acute respiratory illness in immunocompetent patients. J. Am. Coll. Radiol. 2018, 15, S240–S251.

41. Ball, L.; Vercesi, V.; Costantino, F.; Chandrapatham, K.; Pelosi, P. Lung imaging: How to get better look inside the lung. Ann. Transl. Med. 2017, 5, 294.

42. Dennie, C.; Hague, C.; Lim, R.S.; Manos, D.; Memauri, B.F.; Nguyen, E.T.; Taylor, J. Canadian Society of Thoracic Radiology/Canadian Association of Radiologists consensus statement regarding chest imaging in suspected and confirmed COVID-19. Can. Assoc. Radiol. J. 2020, 71, 470–481.

43. Oh, Y.; Park, S.; Ye, J.C. Deep learning COVID-19 features on CXR using limited training data sets. IEEE Trans. Med. Imaging 2020, 39, 2688–2700.

Retrieved from https://encyclopedia.pub/entry/history/show/89787