4

Detection and screening of COVID-19 through chest computed tomography radiographs using deep neural networks.

Khushboo Munir[1], Hassan Elahi[2], Muhammad Umar Farooq[3], Sana Ahmed[4], Fabrizio Frezza[1], Antonello Rizzi[1]

[1]DEPARTMENT OF INFORMATION ENGINEERING, ELECTRONICS AND TELECOMMUNICATIONS, SAPIENZA UNIVERSITY OF ROME, ROME, ITALY; [2]DEPARTMENT OF MECHANICAL AND AEROSPACE ENGINEERING, SAPIENZA UNIVERSITY OF ROME, ROME, ITALY; [3]SURGEON AT DEPARTMENT OF CARDIOLOGY, RAWALPINDI INSTITUTE OF CARDIOLOGY, RAWALPINDI, PAKISTAN; [4]PHYSICIAN AT DEPARTMENT OF MEDICINE, BENAZIR BHUTTO HOSPITAL/ RAWALPINDI MEDICAL UNIVERSITY, RAWALPINDI, PAKISTAN

1. Introduction

Our World has witnessed three most deadly outbreak during the past 18 years, known for hitting the respiratory system and intestine of humans. The first coronavirus outbreak occurred during 2002 named as severe acute respiratory syndrome (SARS-CoV) in Guangdong, China. SARS-CoV originating from China reached about 37 countries affecting 8098 people [1]. After 10 years of this outbreak occurred a second outbreak of coronavirus in the Middle East in 2012, called Middle East respiratory syndrome (MERS-CoV). As of this day, knowledge says that the deadliest number of coronaviruses were originated from Wuhan, China [2], taking over the rest of countries with in weeks. SARS-CoV infected 75,000 people killing 1800 during its first 40 days of outbreak. Where 7000 were found in Wuhan. It was reported that SARS-CoV transmitted into humans from wild animals selling market. Exact source of origin of this virus is still unknown, suggestion says it came from bat [3] and snake [4] (Fig. 4.1).

The year 2019 ended bringing a third and most severe outbreak of new coronavirus disease 2019 pneumonia nick named as COVID-19. This disease originated from the city of Wuhan, China [5–7]. The symptoms of COVID-19 were first summarized by Huang et al. [8] on January 24, 2020. He concluded by studying 41 patients with positive COVID-19 that the most commonly found symptoms are cough, fever, fatigue, and myalgia.

Data Science for COVID-19. https://doi.org/10.1016/B978-0-12-824536-1.00039-3

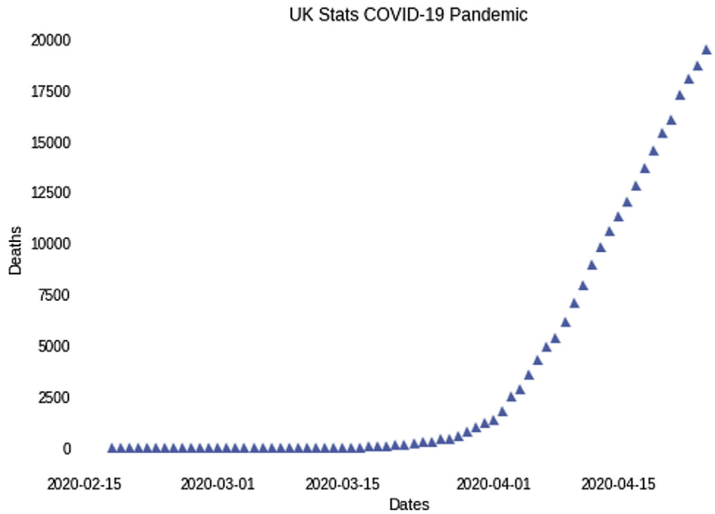

FIGURE 4.1 COVID-19 stats of UK, US, Italy, and China.

These patients suffered through pneumonia and the CT scans of their chest showed abnormalities, along with the complications of acute heart injury, respiratory distress syndrome, and secondary infections. About 32% of patients were transferred to the intensive care unit (ICU) from which 15% patients died. This disease took over the whole world in no time, affecting all human kind. The biggest devastation was caused by this disease in the countries like UK, US, China and Italy (Figs. 4.1 and 4.2) (Table 4.1).

The human-to-human transmission of COVID-19 was first found by a university of Hong-Kong team Kok-KH. There are severe respiratory symptoms associated with COVID-19 causing very high number of ICU admissions decreasing the mortality rate of patients (Fig. 4.2).

Table 4.1 COVID-19 Stats accessed on April 22, 2020. https://coronastats.co/.

Country name	Total infections	Total tests	Recoveries	Deaths	Critical
Russia	57,999	2,250,000	4420	513	700
Spain	208,389	930,230	85,915	21,717	7705
Iran	85,996	377,396	63,113	5391	3311
USA	819,321	4,189,576	83,008	45,356	14,016
Italy	1,450,150	2,250,000	51,600	24,684	2471
Spain	129,044	535,342	0	17,337	17,337
France	158,050	463,662	39,181	20,796	5433
Germany	148,766	1,728,357	99,400	5102	2908

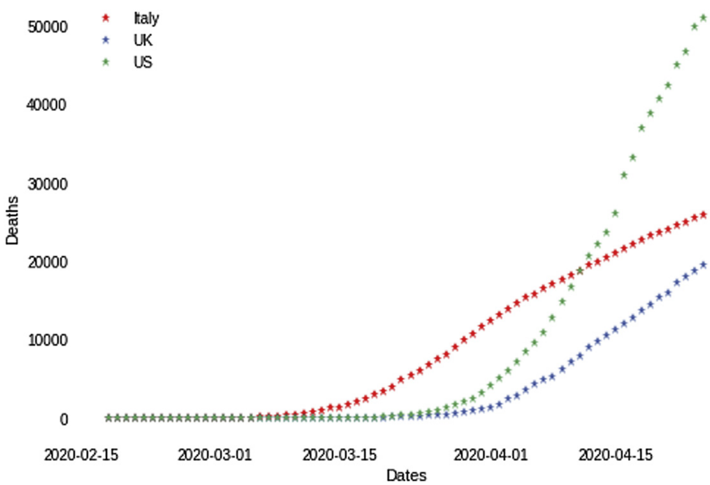

FIGURE 4.2 COVID-19 stats.

COVID-19 pandemic urges for the development of some solution to aid this new coronavirus, thereby inspiring the open source and open access for the AI deep network developers and research community. Some of the networks made for COVID-19 will be discussed below.

Goze et al. [9] developed an initial automated detection method for COVID-19. In their research, they used dataset from the Chinese COVID-19 infected area along with some international multiple datasets. The proposed model uses both three-dimensional (3D) and two-dimensional deep models. The model detects COVID-19 and by using CT feature, it helps in understanding the evolution of COVID-19. Corona Score is generated by evaluating the model over time for COVID-19. 157 international patients including ones from US and China were included for this study. Accuracy achieved by them is 95%, specificity 92.2%, and sensitivity 98.2%. Corona Score is described as the "*progression of disease over time.*"

Loannis et al. [10] studied COVID-19 from transfer learning testing multiple convolutional neural networks. Two types of dataset were used by them; first dataset consisted total X-ray images of 1427 with 700 images of common bacterial pneumonia, 224 confirmed cases of COVID-19, and 504 were with normal conditions. Second data have 714 bacterial confirmed cases, 224 COVID-19 confirmed cases. These two datasets were taken form the pubic repositories. They tested VGG19 [11], Inception [12], MobileNet v2 [13], Xception [14], Inception ResNet v2 [12], and the parameter used for the transfer learning study was layer Cutoff neural network. The accuracy obtained by VGG19 is 98.75%, MobileNet is 97.40%, Inception is 86.13%, Xception is 85.57%, and Inception ResNet v2 is 84.38% for the 2-class. The sensitivity achieved by these networks is 92.85%, 99.10%, 12.94%, 0.08%, and 0.01%, respectively. These networks achieved the specificity of 98.75%, 97.09%, 99.70%, 99.99%, and 99.83%, respectively. MobileNet v2 and VGG19 achieved the best confusion metrix. A deep convolutional neural network was designed by Wang et al. [15] to detect COVID-19 infection from CXR images. The data used is COVIDx which consists of data of 13,645 patients with 16,756 chest radiography images modified from two open data source repositories [16,17]. They made an attempt to discover deep insight for COVID-19 which may help the clinical doctors to improve screening. They achieved the accuracy of 92.6%, sensitivity of normal is 97%, non-COVID-19 is 90%, and for COVID-19 is 87%, whereas the positive prediction value is 89.8% for normal, 94.7% for non-COVID-19, and 96.4% for COVID-19.

Xu et al. [17], formed a model for early screening for differentiating between COVID-19 and viral pneumonia Influenza-A (which includes H3N2, H1N1, H7N9, H5N1, etc). Dataset used consisted of 618 total CT samples, 219 samples were from 110 COVID-19 patients and 224 samples were from 224 Influenza-A patients, the rest 175 were healthy people. Pulmonary CT images were used as an input to the 3D model for segmentation of the infected region at first. Then using the classification model, those segmented images were categorized into Influenza-A, COVID-19, or other infection groups. At the end using the Bayesian or noisy function, final total confidence score is calculated. They achieved the accuracy of 86.7%.

2. Symptoms and characteristics of COVID-19

Treating the COVID-19 patients with current clinical expertise revealed that detection of RT-PCR [18] from the viral RNA from nasopharyngeal swab or sputum in the early stage has low-positive rate. However among all patients with COVID-19, a large number has abnormal chest CT images. The capturing technique used for CT scans of COVID-19 evidently shows that its characteristics are totally different from the other viral pneumonia such as Influenza-A (Table 4.2).

Table 4.2 Pneumonia types and description.

Pneumonia type	Anteroposterior (AP)	Posteroanterior (PA)	Ap Supine
ARDS	0	4	0
Streptococcus spp.	0	11	0
COVID-19	11	76	13
SARS	0	11	0
Pneumocystis spp.	0	1	0

Henceforth in the early diagnosis for this pneumonia, the doctors replaced nucleic acid testing with lung CT as one of the most early approaches. Research done by Chung M et al. [19] and Jeffrey Kanne [20] showed COVID-19's striking peripheral distribution with pleura and ground-glass appearance.

3. Screening for COVID-19

There are devastating effects of COVID-19 pandemic on the human population globally. Screening for the infected is a most crucial step in the war against COVID-19. Those found infected needs to be separated, isolated, and treated to stop the spread of virus.

3.1 Polymerase chain reaction

Screening method which is mainly being used for COVID-19 detection is polymerase chain reaction (PCR) testing [21–23]. In this method, the RNA of SARS-CoV-2 is detected from the respiratory specimens which can be collected through oropharyngeal swabs or nasopharyngeal. PCR method is a highly sensitive gold standard method but its complicated, laborious, and time-consuming manual process providing very short supply.

3.2 Radiography

Chest radiography images have been used as an alternative approach for COVID-19 detection [24–26] such as computed tomography (CT) [27–29]images of X-ray images. Visual indications are being analyzed manually by radiologist who found the chest abnormalities in the chest radiography images of the COVID-19 infected patients [9,30]. Radiography is a fast testing system with high sensitivity considering the imaging techniques of the modern health care system as compared to PCR testing.

4. Deep model for COVID-19 detection

4.1 Data acquisition

The need of fast testing systems for detecting COVID-19 from radiography images artificial intelligence (AI) systems is the need to jump in to tackle the problem [31]. Considering this pandemic situation, a number of deep learning systems have been proposed for COVID-19 detection via radiography images [22].

The source data which have been used for these researches are kept confidential and not made available for the rest of research community for the aid of better and deep understanding of the system being proposed and future extensions of that work. The public access also not made public making it more crucial to push the open access for AI and open source solutions for COVID-19 detection. Cohen et al. [16] made effort to built chest X-ray Dataset for COVID-19 consisting of SARS and MERS cases in addition to COVID-19 cases, so that a correct classification can be studied. Data images used are

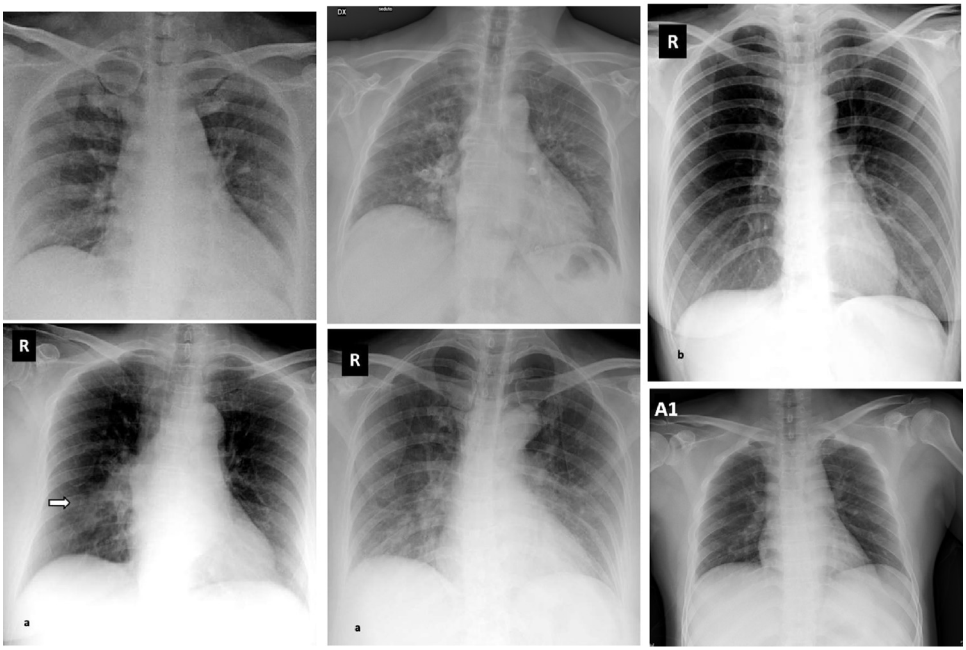

FIGURE 4.3 X-ray Images of COVID-19 positive patients.

from the github source: **URL**: https://github.com/ieee8023/covid-chestxray-dataset. The Chest X-ray 14 by Wang et al. [32] helped to develop the tools to predict pneumonia and its outcome. The X-ray images of COVID-19 are shown in Fig. 4.3, whereas normal X-ray images are shown in Fig. 4.4. Rajpurker et al. [33] and Cohen et al. [34] worked on the prediction of pneumonia.

5. Preprocessing

The given data consisted of 112 COVID-19 patients X-ray images and 112 normal patients X-ray images for training, therefore in the preprocessing, data augmentation is implemented as shown in Table 4.3.

6. Experiment

6.1 Model architecture

We present a deep network with six blocks. Each block consists of a convolutional layer with filter stride of (3,3) and relu activation, max pooling layer with pool size (2,2), and a dropout of 0.2. A flatten layer is added with dropout 0.5 followed by a dense layer with sigmoid activation. Total trainable parameters in our network are 7,338,817.

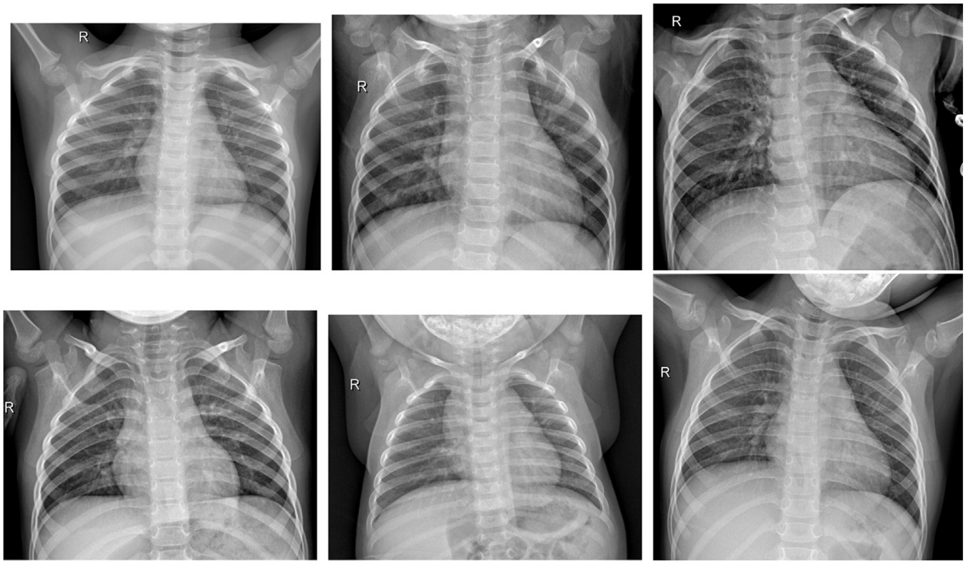

FIGURE 4.4 Normal X-ray images.

Table 4.3 Data Augmentation metrics.

Rescaling	1/255
Shear range	0.2
Zoom range	0.2
Horizontal flip	True

6.2 Training and results

The model is trained with the 224 images subjected to data augmentation. Training accuracy achieved by this model is 0.835, and training loss is 0.244. Whereas the validation accuracy is 0.95 and validation loss is 0.22. The model accuracy and loss is shown in Figs. 4.5 and 4.6,. Confusion matrix in shown in Fig. 4.7 in which 0 represents the COVID-19 cases and 1 represents normal cases.

7. Discussion and conclusion

During the pandemic situation such as COVID-19, it is crucial to slower down the spread to buy some time for the research and antivirus preparation. Hence there is a need of a timely diagnosis of the disease and taking the necessary steps to contain the virus and stop the spread. Laboratory testing based on nucleic acid has many limitations which urges for the new methods of diagnosis for the front-line health officials to act promptly

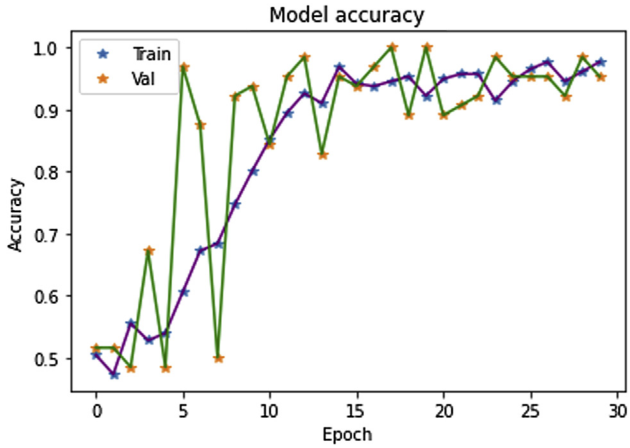

FIGURE 4.5 Model accuracy.

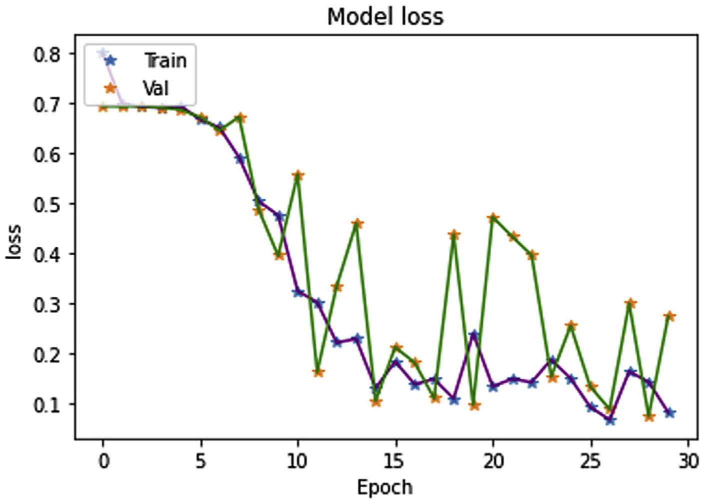

FIGURE 4.6 Model loss.

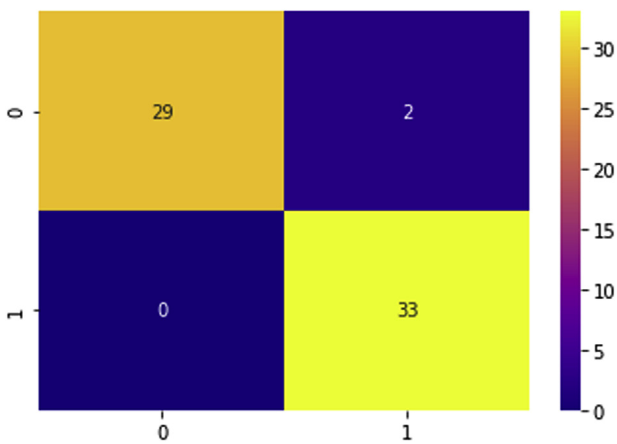

FIGURE 4.7 Confusion matrix “Covid:0” and “Normal:1.”

and quickly. Therefore the AI methods are developed which are discussed in this chapter. Using the deep learning algorithms and with CT chest radiographs, alternative methods for diagnosis of COVID-19 have been made. These diagnostic solutions are time efficient with respect to the clinical methods. Although these algorithms are trained and tested on a very small amount of data, as there is no detailed repository yet made with large COVID-19 patients data. The international research community is collaborating efficiently to create a data repository to aid the researchers for deep learning solution development. Data solutions are also discussed in this study.

Nucleic acid—based testing is very respectful, but it has drawbacks such as, the fact that, specimen collection delays the disease diagnosis, which in turn delays the disease control making the situation worse. Current study data show that the max accuracy achievable from nucleic acid testing is 30%—50% whereas the deep learning methods based on extraction of features from CT images can achieve the accuracy up to 83%, which outperforms this clinical method.

With the passage of time when large number of data will be provided to the research community, then it would be possible to achieve highly reliable results from AI for COVID-19. This will help to achieve an optimized diagnostic system. In future, some factors must be included for the study of COVID-19 such as multimodel analysis, genetic feature, clinical information, multiomics, epidemiological features, etc., to make AI more profitable in terms of providing the best diagnostic systems for COVID-19, helping the healthcare to tackle the pandemic.

8. Current research and future work

In this research article, we presented different method which can be used for the detection of COVID-19; in addition, we proposed a deep neural network for COVID-19 detection. Our work achieved promising accuracy because of lack of large public data; these results cannot be currently compared with other methods being proposed. As soon as a large public repository is formed, the model results will have the opportunity of comparison. In future, we will try to access more data and make our model more deep and try to make it more efficient.

References

[1] J. Cui, F. Li, Z.-L. Shi, Origin and evolution of pathogenic coronaviruses, Nat. Rev. Microbiol. 17 (3) (2019) 181—192.

[2] S. Khan, R. Siddique, A. Ali, M. Xue, G. Nabi, Novel coronavirus, poor quarantine, and the risk of pandemic, J. Hosp. Infect. 104 (4) (2020) 449—450.

[3] P. Zhou, X.-L. Yang, X.-G. Wang, B. Hu, L. Zhang, W. Zhang, H.-R. Si, Y. Zhu, B. Li, C.-L. Huang, et al., A pneumonia outbreak associated with a new coronavirus of probable bat origin, Nature 579 (7798) (2020) 270—273.

[4] W. Ji, W. Wang, X. Zhao, J. Zai, X. Li, Cross-species transmission of the newly identified coronavirus 2019-ncov, J. Med. Virol. 92 (4) (2020) 433—440.

[5] N. Zhu, D. Zhang, W. Wang, X. Li, B. Yang, J. Song, X. Zhao, B. Huang, W. Shi, R. Lu, et al., China novel coronavirus investigating and research team. a novel coronavirus from patients with pneumonia in China, 2019, N. Engl. J. Med. 382 (8) (2020) 727−733.

[6] R. Thompson, Pandemic potential of 2019-ncov, Lancet Infect. Dis. 20 (3) (2020) 280.

[7] J. Cohen, D. Normile, New Sars-like Virus in china Triggers Alarm, 2020.

[8] C. Huang, c Huang, y wang, x li, et al., Clinical Features of Patients Infected with, 2019, pp. 497−506.

[9] O. Gozes, M. Frid-Adar, H. Greenspan, P.D. Browning, H. Zhang, W. Ji, A. Bernheim, E. Siegel, Rapid Ai Development Cycle for the Coronavirus (Covid-19) Pandemic: Initial Results for Automated Detection & Patient Monitoring Using Deep Learning Ct Image Analysis, 2003, p. 05037, arXiv preprint arXiv.

[10] I.D. Apostolopoulos, T.A. Mpesiana, Covid-19: automatic detection from x-ray images utilizing transfer learning with convolutional neural networks, Phys. Eng. Sci. Med. (2020) 1.

[11] K. Simonyan, A. Zisserman, Very Deep Convolutional Networks for Large-Scale Image Recognition, 2015 arXiv preprint arXiv:1409.1556.

[12] C. Szegedy, S. Ioffe, V. Vanhoucke, A.A. Alemi, Inception-v4, inception-resnet and the impact of residual connections on learning, in: Thirty-first AAAI Conference on Artificial Intelligence, 2017.

[13] A.G. Howard, M. Zhu, B. Chen, D. Kalenichenko, W. Wang, T. Weyand, M. Andreetto, H. Adam, Mobilenets: Efficient Convolutional Neural Networks for Mobile Vision Applications, 2017 arXiv preprint arXiv:1704.04861.

[14] F. Chollet, Xception: deep learning with depthwise separable convolutions, in: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2017, pp. 1251−1258.

[15] L. Wang, A. Wong, Covid-net: A Tailored Deep Convolutional Neural Network Design for Detection of Covid-19 Cases from Chest Radiography Images, 2003, p. 09871, arXiv preprint arXiv.

[16] T. Ai, Z. Yang, H. Hou, C. Zhan, C. Chen, W. Lv, Q. Tao, Z. Sun, L. Xia, Correlation of chest Ct and Rt-Pcr testing in coronavirus disease 2019 (Covid-19) in China: a report of 1014 cases, Radiology (2020) 200642.

[17] X. Xu, X. Jiang, C. Ma, P. Du, X. Li, S. Lv, L. Yu, Y. Chen, J. Su, G. Lang, et al., Deep Learning System to Screen Coronavirus Disease 2019 Pneumonia, 2002, p. 09334, arXiv preprint arXiv.

[18] V.M. Corman, O. Landt, M. Kaiser, R. Molenkamp, A. Meijer, D.K. Chu, T. Bleicker, S. Brünink, J. Schneider, M.L. Schmidt, et al., Detection of 2019 novel coronavirus (2019-ncov) by real-time rt-pcr, Euro Surveill. 25 (3) (2020) 2000045.

[19] M. Chung, A. Bernheim, X. Mei, N. Zhang, M. Huang, X. Zeng, J. Cui, W. Xu, Y. Yang, Z.A. Fayad, et al., Ct imaging features of 2019 novel coronavirus (2019-ncov), Radiology 295 (1) (2020) 202−207.

[20] J.P. Kanne, Chest Ct Findings in 2019 Novel Coronavirus (2019-ncov) Infections from Wuhan, china: Key Points for the Radiologist, 2020.

[21] G.D. Rubin, C.J. Ryerson, L.B. Haramati, N. Sverzellati, J.P. Kanne, S. Raoof, N.W. Schluger, A. Volpi, J.-J. Yim, I.B. Martin, et al., The Role of Chest Imaging in Patient Management during the Covid-19 Pandemic: A Multinational Consensus Statement from the Fleischner Society, Chest, 2020.

[22] Y. Fang, H. Zhang, J. Xie, M. Lin, L. Ying, P. Pang, W. Ji, Sensitivity of chest Ct for Covid-19: comparison to Rt-Pcr, Radiology (2020), 200432.

[23] X. Xie, Z. Zhong, W. Zhao, C. Zheng, F. Wang, J. Liu, Chest Ct for typical 2019-ncov pneumonia: relationship to negative Rt-Pcr testing, Radiology (2020) 200343.

[24] J. Deng, W. Dong, R. Socher, L.-J. Li, K. Li, L. Fei-Fei, Imagenet: a large-scale hierarchical image database, in: 2009 IEEE Conference on Computer Vision and Pattern Recognition, Ieee, 2009, pp. 248−255.

[25] S. Chaganti, A. Balachandran, G. Chabin, S. Cohen, T. Flohr, B. Georgescu, P. Grenier, S. Grbic, S. Liu, F. Mellot, et al., Quantification of Tomographic Patterns Associated with Covid-19 from Chest Ct, 2004, p. 01279, arXiv preprint arXiv.

[26] L. Huang, R. Han, T. Ai, P. Yu, H. Kang, Q. Tao, L. Xia, Serial quantitative chest ct assessment of covid-19: deep-learning approach, Radiology 2 (2) (2020) e200075.

[27] G. Chassagnon, M. Vakalopoulou, N. Paragios, M.-P. Revel, Artificial intelligence applications for thoracic imaging, Eur. J. Radiol. 123 (2020) 108774.

[28] A.M. Hafiz, G.M. Bhat, A survey of deep learning techniques for medical diagnosis, in: Information and Communication Technology for Sustainable Development, Springer, 2020, pp. 161–170.

[29] K. Munir, H. Elahi, A. Ayub, F. Frezza, A. Rizzi, Cancer diagnosis using deep learning: a bibliographic review, Cancers 11 (9) (2019) 1235.

[30] L. Li, L. Qin, Z. Xu, Y. Yin, X. Wang, B. Kong, J. Bai, Y. Lu, Z. Fang, Q. Song, et al., Artificial intelligence distinguishes Covid-19 from community acquired pneumonia on chest Ct, Radiology (2020) 200905.

[31] C. Huang, Y. Wang, X. Li, L. Ren, J. Zhao, Y. Hu, L. Zhang, G. Fan, J. Xu, X. Gu, et al., Clinical features of patients infected with 2019 novel coronavirus in Wuhan, China, Lancet 395 (10223) (2020) 497–506.

[32] X. Wang, Y. Peng, L. Lu, Z. Lu, M. Bagheri, R.M. Summers, Chestx-ray8: hospital-scale chest x-ray database and benchmarks on weakly-supervised classification and localization of common thorax diseases, in: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2017, pp. 2097–2106.

[33] P. Rajpurkar, A.Y. Hannun, M. Haghpanahi, C. Bourn, A.Y. Ng, Cardiologist-level Arrhythmia Detection with Convolutional Neural Networks, 2017 arXiv preprint arXiv:1707.01836.

[34] J.P. Cohen, P. Bertin, V. Frappier, Chester: A Web Delivered Locally Computed Chest X-Ray Disease Prediction System, 2017 arXiv preprint arXiv:1901.11210.