Comparative study for automated coronavirus detection in CT images with transfer learning

Nisreen Sulayman[1]

Abstract

Purpose: To design a computer-aided diagnosis system with transfer learning methods to serve as decision support system for automated coronavirus detection in CT images.

Methods: Four pre-trained deep convolutional neural networks (ResNet-18, SqueezeNet, ShuffleNet, MobileNet-v2) have been investigated to diagnose coronavirus with CT scans. To evaluate the pre-trained deep convolutional neural network, we used the COVID-CT dataset, which contains 349 CT images of COVID-19 from 216 patients, and 397 CT images obtained from non-COVID-19 subjects.

Results: Considering binary classification performance results, it has been seen that the pre-trained ResNet-18 model provides the highest classification performance (97.0470 ± 5.5466 accuracy, 98.7342 ± 2.1925 sensitivity, 95.1429 ± 9.3460 specificity, and 0.9737± 0.0489 F1-score) among other three used models.

Conclusion: ResNet-18 model can be employed as a supportive decision-making system to assist radiologists at clinics and hospitals to screen patients swiftly.

Keywords: Coronavirus, Transfer learning, ResNet-18, COVID-CT dataset.

(1) Biomedical Engineering Department, Mechanical and Electrical Engineering Faculty, Damascus University, Damascus, Syria. sulayman.nisreen@gmail.com, nisreen.sulayman@damascusuniversity.edu.sy
Faculty of Dentistry, Syrian Private University, Damascus, Syria. , nisreen.sulayman@spu.edu.sy

دراسة مقارنة للكشف الآلي عن فيروس كورونا في صور المقطعي المحوسب باستخدام نقل التعليم

نسرين سليمان[1]

الملخص

الهدف: تنفيذ نظام تشخيص بمساعدة الحاسوب باستخدام نقل التعليم لدعم قرار الطبيب في الكشف الآلي عن فيروس كورونا في صور المقطعي المحوسب.

الطرائق: تم دراسة أربع شبكات عصبونية مدربة مسبقاً (ResNet-18, SqueezeNet, ShuffleNet MobileNet-v2) باسخدام نقل التعليم بهدف تشخيص فيروس كورونا في صور المقطعي المحوسب. تم اختبار أداء الشبكات العصبونية المذكورة من خلال تطبيقها على قاعدة بيانات صور مقطعي محوسب للرئتين مؤلفة من 349 صورة ل 216 مريض كورونا و379 صورة لأمراض مختلفة لا تشمل فيروس كورونا.

النتائج: أوضحت نتائج بارامترات قياس أداء التصنيف الثنائي تفوق أداء الشبكة العصبونية ResNet-18 في التصنيف مقارنة مع باقي الشبكات العصبونية موضع الدراسة وفقاً للقيم التالية: دقة 97.0470 ± 5.5466، حساسية 98.7342 ± 2.1925، نوعية 95.1429 ± 9.3460، ومعامل (F1) 0.0489 ±0.9737.

الاستنتاج: يمكن استخدام الشبكة العصبونية ResNet-18 كنظام لدعم قرار طبيب الأشعة في تشخيص فيروس كورونا في العيادات والمستشفيات.

الكلمات المفتاحية: نقل التعليم، الشبكة العصبونيةResNet-18، قاعدة بيانات تصوير مقطعي محوسب لفيروس كورونا.

(1) مدرس في قسم الهندسة الطبية، كلية الهندسة الميكانيكية والكهربائية، جامعة دمشق، سوريا.
nisreen.sulayman@damascusuniversity.edu.sy sulayman.nisreen@gmail.com
مدرس في كلية طب الأسنان، الجامعة السورية الخاصة nisreen.sulayman@spu.edu.sy

1. Introduction

Coronavirus disease 2019 (COVID-19) has caused 4,777,503 deaths all over the globe, among 233,503,524 confirmed cases, as of 1st October 2021 [1].

Early diagnosis of this disease within the preliminary stages is critical. One major hurdle in controlling the spreading of COVID-19 disease is that the shortage of tests. The current tests mostly rely on reverse transcription polymerase chain reaction (RT-PCR). RT-PCR is considered the gold standard for early detection of COVID-19 [2]. However, performing the RT-PCR test needs equipped laboratories (that are not available in most countries). Also, the test result may require retaking the RT-PCR or other tests [3].

During the COVID-19 outbreak, RT-PCR test kits were in great shortage. As a result, many suspected cases cannot be tested at the proper time, and therefore may contribute to the spread of the disease. Hospitals are utilizing alternative diagnosis methods to mitigate the shortage of RT-PCR test kits, and are using computerized tomography (CT) scans for diagnosing COVID-19. Doctors use CT scans to judge whether a patient is infected by viral pneumonia. Although, CTs lacks the ability to specify which virus is causing viral pneumonia. During the outbreak time, if a doctor diagnosed that a patient has viral pneumonia according to CT results, this pneumonia is very likely to be COVID-19 [4].

Researchers highly regarded the design of computer-aided diagnosis systems (CADs) based on AI (artificial intelligence) using CT scan images for precise diagnosis of COVID-19 [5-7]. Deep learning (DL) is a subfield of AI, and many research articles have been published on its application for diagnosing COVID-19 [8].

The main contribution of this research is summarized as follows:

- A high-accuracy decision support system depending on a selected pre-trained neural network (with low computational cost) has been proposed to radiologists for the diagnosis and detection of suspected coronavirus.
- The low computational cost of the selected model helps to make it applicable in various cities and countryside which improve controlling the spreading of pandemic in more efficient way.
- The decision support system accelerates the diagnosing process and elevates the accuracy of diagnosis.

The rest of this paper is arranged as follows: The related studies are discussed in section 2. A detailed description of the materials and methods is shown in section 3. Section 4 demonstrates the experimental results and evaluation. Section 5 presents a discussion about the results and compares them with the previously obtained from the literature**.** This paper is concluded in section 6.

2. Related work

Deep learning algorithms, in particular convolutional networks, have rapidly become a methodology for analyzing medical images [9].

Panahi et al. (2021) proposed a novel technique called Fast COVID-19 Detector (FCOD) to detect COVID-19 using X-ray images. The FCOD is a deep convolutional neural network (CNN) model based on the Inception architecture. The network can automatically recognize the complicated patterns from X-ray images. The model classified the COVID-19 virus and achieved a lower cost process and prediction time [10].

Liu et al. (2021) proposed a two-stage transfer learning framework for segmenting COVID-19 lung infections from CT images. The framework learned valuable knowledge from both natural images and CT images with pulmonary nodules, allowing more effective network training for improved performance. They developed an infection segmentation network, called nCoVSegNet [11].

Narin et al. (2021) implemented an automatic detection algorithm of coronavirus disease (COVID-19) using X-ray images and deep convolutional neural networks, they used five pre-trained convolutional neural network (CNN)-based models (ResNet50, ResNet101, ResNet152, InceptionV3, and Inception-ResNetV2) for the detection of coronavirus pneumonia infected patient from chest X-ray images [12].

Maghdid et al. (2021) built a comprehensive dataset of X-ray and CT scan images from multiple sources. They provided a COVID-19 detection technique using deep learning and transfer learning algorithms and modified the pre-trained AlexNet model and applied it on the prepared images in the dataset [13].

Wang et al. (2020) implemented a deep learning method that could extract COVID-19's graphical features from CT images to provide a clinical diagnosis ahead of the pathogenic test. They modified the Inception transfer-learning model to establish the algorithm, followed by internal and external validation [14].

Li et al. (2020) developed an automatic framework to detect coronavirus using CT images and evaluate its performance. They developed the COVID-19 detection neural network (COVNet) to extract pictorial features from volumetric chest CT images for the detection of COVID-19. CT scans of community-acquired pneumonia (CAP) and other non-pneumonia abnormalities were used to test the the model. They concluded that the proposed model can accurately detect coronavirus 2019 and differentiate it from CAP and other lung conditions [15].

Song et al. (2021) collected chest CT scans of 88 patients diagnosed with the COVID-19. Based on the collected dataset, they implemented a deep learning-based CT diagnosis system (DeepPneumonia) to identify patients with COVID-19. Each CT image is input to the pre-trained ResNet50 model to extract local and global features [16].

3. Materials and methods

3.1. COVID-CT dataset

The COVID-19 CT dataset used in this study is publicly available on GitHub repository [17], and its details are described in [4]. The dataset consists of 349 chest CT images of COVID-19 from 216 patients, and 397 CT images from non-COVID-19 subjects. Figure 1 shows chest CT images of COVID-19 and non-COVID-19 subjects.

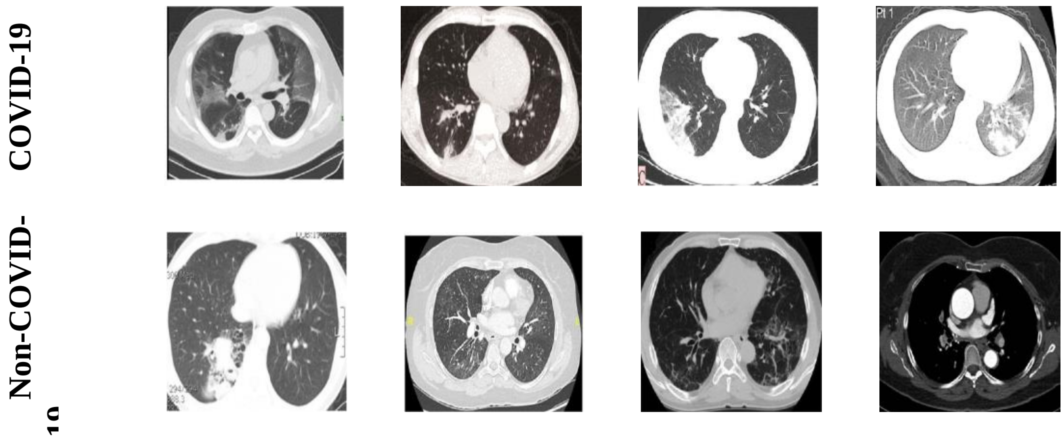

Figure (1). Examples of chest CT images [17]. The first row shows CT images diagnosed with COVID-19, whereas the second row shows examples of non-COVID-19 cases, but other lung diseases. (Aspect ratios of some images were rescaled for display purposes only).

3.2. The networks architecture

This section describes the deep pre-trained architectures utilized to identify COVID-19 using chest CT scans. These networks are state-of-the-art deep CNN models for image recognition. They differ in their architectural design to achieve better power and to reduce their computational complexity. Table 1 shows the pre-trained deep neural networks trained on ImageNet and some of their properties. The inputs to all networks are RGB images.

Table (1). Characteristics of the deep pre-trained CNNs architectures [18].

Network	Depth (# of layers)	Size (MB)	Parameters (Millions)	Image Input Size
squeezenet	18	5.2	1.24	227-by-227
googlenet	22	27	7.0	224-by-224
inceptionv3	48	89	23.9	299-by-299
densenet201	201	77	20.0	224-by-224
mobilenetv2	53	13	3.5	224-by-224
resnet18	18	44	11.7	224-by-224
resnet50	50	96	25.6	224-by-224
resnet101	101	167	44.6	224-by-224
xception	71	85	22.9	299-by-299
inceptionresnetv2	164	209	55.9	299-by-299
shufflenet	50	5.4	1.4	224-by-224
nasnetmobile	*	20	5.3	224-by-224
nasnetlarge	*	332	88.9	331-by-331
darknet19	19	78	20.8	256-by-256
darknet53	53	155	41.6	256-by-256
efficientnetb0	82	20	5.3	224-by-224
alexnet	8	227	61.0	227-by-227
vgg16	16	515	138	224-by-224
vgg19	19	535	144	224-by-224

In this work, I considered the most advanced networks, such as SqueezeNet [19], ShuffleNet [20], MobileNet-v2 [21], and ResNet-18 [22]. I elected these pre-trained CNNs to be investigated for their low computational cost and time considering the number of parameters in each model. Figure 2 shows visual representation of the number of parameters given in Millions for each of the pre-trained neural network depicted in table 1.

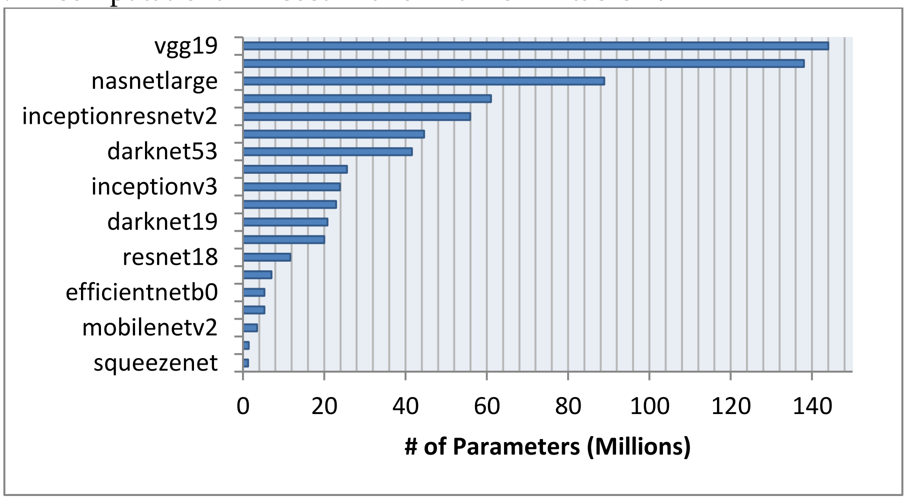

Figure (2). Visual representation of the number of parameters given in Millions for different pre-trained neural networks.

Researchers have trained the pre-trained image classification deep CNNs on over a million images and can classify images into 1000 object categories. The CNNs have learned rich feature representations for a wide range of images. Each network takes an image as input and then outputs a class for the object in the image.

3.3. Transfer learning

Transfer learning is used in deep learning applications. A pre-trained deep CNN network is used as a starting point to learn a new task. Figure 3 shows the transfer learning process by reusing a pre-trained neural network [22].

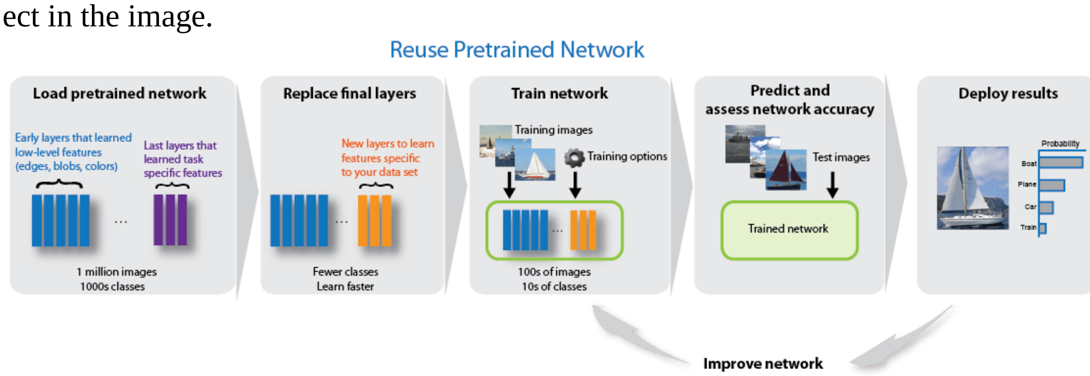

Figure (3). Transfer learning: reuse pre-trained network [18].

3.4. Experimental settings

The dataset was shuffled and split into 80% for training and 20% for testing. To assess the performances of our models, we performed K-fold cross-validation with K = 5 to keep the distribution of the two classes consistent in each fold. The final performances of the models were computed by averaging the obtained values from the four networks on their test folds respectively. To enable the reproduction of the results reported in this study, configurations for transfer learning are described as follows.

First, the layer graph from the deep network was extracted. The last layer with learnable weights in most pre-trained networks is a fully connected layer. This fully connected layer was extracted and replaced with a new fully connected layer with the number of outputs equal to the number of labels in the new data set, which is two, in this study. In some pre-trained networks, such as SqueezeNet, the last learnable layer is a 1-by-1 convolutional layer instead. For the SqueezeNet, the convolutional layer was replaced with a new convolutional layer with the number of filters equal to the number of classes.

Second, the classification layer which identifies the output labels of the network was replaced with a new one without class labels. The output classes of the new classification layer were automatically set at training time.

As the pre-trained CNNs explicitly require an RGB input, identical values were assigned to the R, G, and B channels. Since the chest CT images in the COVID-CT dataset have varying spatial sizes, the images are rescaled to match the target CNN input size. Considering the training options, the stochastic gradient descent with momentum value equals 0.9000. Table 2 lists the training options.

Table (2). Training options.

Property	Value
Gradient threshold method	'l2norm'
Initial learn rate	3.0000e-04
Max epochs	6
Minimum batch size	10
Shuffle	'every-epoch'
Verbose	0

3.5. Experimental evaluation

Different performance evaluation metrics are considered for evaluating the binary classification performance of the pre-trained CNNs. The evaluating metrics are accuracy, sensitivity, specificity, and F1 score. Sensitivity is the percentage of COVID-19 patients who are correctly identified as having the infection. Specificity is the percentage of non-COVID-19 subjects who are correctly classified as having no infection of COVID-19. Equations (1)-(4) refer to the definition of each metric.

$$Sensitivity = \frac{TP}{TP + FN} \times 100\% \quad (1)$$

$$\mathrm{Specificit\ y} = \frac{\mathrm{TN}}{\mathrm{TN} + \mathrm{FP}} \times 100\% \quad (2)$$

$$Accuracy = \frac{TP + TN}{TP + FN + TN + FP} \times 100\% \quad (3)$$

$$F1 - score = \frac{2TP}{2TP + FN + FP} \times 100\% \quad (4)$$

where TP is called true positive, denoting the number of COVID-19 patients who are correctly identified as having the infection, FN is called false negative, determines the number of COVID-19 patients who are misclassified as having no infection of COVID-19, and (TP+FN) is the total number of COVID-19 patients. TN is called true negative and denotes the number of non-COVID-19 subjects who are correctly identified as having no infection of COVID-19, FP is called false positive, denoting the number of non-COVID-19 subjects who are misclassified as having the infection, and (TN+FP) is the total number of non-COVID-19 subjects. Accuracy is the percentage of correct classification, F1 score is the balance between precision (TP divided by TP and FP) and sensitivity.

4. Results

Here, we present the results for detecting COVID-19 on the considered CT image dataset (349 CT images of COVID-19, and 397 CT images obtained from non-COVID-19 subjects) using our four fine-tuned deep CNNs networks. Table 3 summarizes the average values of evaluation metrics achieved by our different networks on the CT image dataset. The network training was performed without data augmentation. The best values results are depicted in bold.

Table (3). Classification results of 5-fold cross-validation. The results are given in the form of mean and standard deviation score.

CNN model	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1 score
SqueezeNet	86.9799±7.2378	85.8228± 10.2602	88.2857±16.7027	0.8755±0.0625
ShuffleNet	96.1074±5.7812	94.9367±7.8031	97.4286±3.5571	0.9617±0.0574
ResNet-18	**97.0470 ± 5.5466**	**98.7342 ± 2.1925**	**95.1429 ± 9.3460**	**0.9737±0.0489**
MobileNet-v2	96.3758±3.8729	96.2025±5.3704	96.5714±3.5857	0.9653±0.0374

ResNet-18 achieves the best overall performance with respect to all the evaluation metrics, with an average accuracy of 97.0470±5.5466 and F1-score of 0.9737±0.0489 . The model also achieves an average sensitivity rate of 98.7342 ± 2.1925 and correctly identifies almost all non-COVID-19 cases resulting in a specificity rate of 95.1429 ± 9.3460.

The SqueezeNet model obtains the lowest performance with respect to all evaluation metrics with a fairly acceptable average accuracy and sensitivity scores of 86.9799±7.2378 and 85.8228± 10.2602 respectively.

5. Discussion

The work published in [23] applied 12 pre-trained deep CNN using COVID-CT dataset with the same value of cross-validation (k=5), reported among all the 12 networks, DensNet201 was the best for classification task. DensNet201 model achieved accuracy of 92.9 ± 2.2 %, specificity =92.2 ± 2.2, sensitivity =93.7 ± 3.4, and F1 score=92.5 ± 2.4. However, the study published in [23] implemented data augmentation methods, such as cropping, adding blur with a probability of 25%, adding a random amount of Gaussian noise, changes in brightness and contrast, and random horizontal flipping which increased computational complexity and running time.

The study reported in [24] requires regions of interest (ROI) segmentation and the segmented regions were then employed as an additional input to six deep convolutional neural network architectures (AlexNet, DenseNet, GoogleNet, NASNet-Mobile, ResNet18, and DarkNet), to differentiate between COVID-19 and non-COVID-19 CT images. For the COVID-CT dataset, DarkNet CNN model attained the best accuracy of 82.80%. Table 4 shows the average values of performance evaluation metrics achieved by the proposed model in this study (ResNet-18) and compares the results with the previously obtained results from the literature using the same COVID-19 CT dataset when applicable.

Table (4). Performance evaluation metrics comparison of different deep models for detecting COVID-19 using various evaluation metrics. The results are submitted in the form of mean and standard deviation scores.

Reference	CNN model	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1 score (%)
[23]	SqueezeNet	87.3 ± 3.2	86.5 ± 2.3	87.9 ± 6.3	86.5 ± 3.0
	ShuffleNet	87.9 ± 2.6	90.8 ± 3.9	85.4 ± 2.7	87.6 ± 2.8
	ResNet50	90.8 ± 1.9	90.0 ± 3.6	91.4 ± 5.0	90.1 ± 1.9
	DenseNet201	92.9 ± 2.2	93.7 ± 3.4	92.2 ± 2.2	92.5 ± 2.4
[25]	EfficientNetB0	82 ± 2	82.2 ±11	-	81.5 ± 5
	EfficientNetB5	82 ± 3	81.7 ±11	-	81.7 ± 5
	ResNet50	81 ± 3	80.8 ±11	-	80.7 ± 5
	DenseNet121	77 ± 2	76.8 ± 3	-	76.8 ± 3
[26]	ResNet-101	80.3	85.7	-	81.8
[27]	DenseNet169	87.7 ± 4.7	85.6±6.7	-	87.8 ± 5.0
[28]	LeNet-5	86.06	89	-	87
This study	ResNet-18	97.04 ± 5.55	98.73 ± 2.19	95.14 ± 9.35	97.37 ± 4.89

The low computational cost and high performance of the ResNet-18 help to make it applicable in rural areas of cities which lead to reduce the number of COVID-19 patients who can spread the virus to other people.

6. Conclusion

Researchers consider AI-based medical diagnosis systems based on deep learning of medical imaging to be clinically useful. However, the development of suitable deep-learning networks and effective training strategies for clinical applications is a topic of research that needs to be explored. This study discovers the very high performance of the network for COVID-19 diagnosis using CT images with low computational cost and time due to the small number of parameters of the proposed model among other available pre-trained CNN models. The network configuration of the pre-trained model can be implemented for the classification of other image modalities, such as X-ray, for the detection of COVID-19.

The findings reported from this study contribute to the development of fast and efficient diagnostic tools using imaging data, and to further leading into the development of more accurate point-of-care diagnostic and detection tools for containing the coronavirus pandemic.

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Declaration of Competing Interest

None

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References

[1] WHO Coronavirus (COVID-19) Dashboard, https://covid19.who.int/ (1 October 2021)

[2] Tahamtan, A., & Ardebili, A. (2020). Real-time RT-PCR in COVID-19 detection: issues affecting the results. Expert review of molecular diagnostics, 20(5), 453-454. https://doi.org/10.1080/14737159.2020.1757437

[3] Ozturk, T., Talo, M., Yildirim, E. A., Baloglu, U. B., Yildirim, O., & Acharya, U. R. (2020). Automated detection of COVID-19 cases using deep neural networks with X-ray images. Computers in biology and medicine, 121, 103792. https://doi.org/10.1016/j.compbiomed.2020.103792

[4] Yang X, He X, Zhao J, Zhang Y, Zhang S, Xie P.(2020). COVID-CT-dataset: A CT scan dataset about covid-19. arXiv preprint arXiv:2003.13865, 490.

[5] Islam, M. M., Karray, F., Alhajj, R., & Zeng, J. (2021). A review on deep learning techniques for the diagnosis of novel coronavirus (covid-19). IEEE Access, 9, 30551-30572. https://doi.org/10.1109/ACCESS.2021.3058537

[6] Salehi, A. W., Baglat, P., & Gupta, G. (2020). Review on machine and deep learning models for the detection and prediction of Coronavirus. Materials Today: Proceedings, 33, 3896-3901. https://doi.org/10.1016/j.matpr.2020.06.245

[7] Chaudhary, P. K., & Pachori, R. B. (2020, December). Automatic diagnosis of COVID-19 and pneumonia using FBD method. In 2020 IEEE International Conference on Bioinformatics and Biomedicine (BIBM) (pp. 2257-2263). IEEE. https://doi.org/10.1109/BIBM49941.2020.9313252

[8] Swapnarekha, H., Behera, H. S., Nayak, J., & Naik, B. (2020). Role of intelligent computing in COVID-19 prognosis: A state-of-the-art review. Chaos, Solitons & Fractals, 138, 109947. https://doi.org/10.1016/j.chaos.2020.109947

[9] Litjens, G., Kooi, T., Bejnordi, B. E., Setio, A. A. A., Ciompi, F., Ghafoorian, M., & Sánchez, C. I. (2017). A survey on deep learning in medical image analysis. Medical image analysis, 42, 60-88. https://doi.org/10.1016/j.media.2017.07.005

[10] Panahi, A. H., Rafiei, A., & Rezaee, A. (2021). FCOD: Fast COVID-19 Detector based on deep learning techniques. Informatics in Medicine Unlocked, 22, 100506. https://doi.org/10.1016/j.imu.2020.100506

[11] Liu, J., Dong, B., Wang, S., Cui, H., Fan, D. P., Ma, J., & Chen, G. (2021). COVID-19 lung infection segmentation with a novel two-stage cross-domain transfer learning framework. Medical Image Analysis, 74, 102205. https://doi.org/10.1016/j.media.2021.102205

[12] Narin, A., Kaya, C., & Pamuk, Z. (2021). Automatic detection of coronavirus disease (covid-19) using x-ray images and deep convolutional neural networks. Pattern Analysis and Applications, 1-14. https://doi.org/10.1007/s10044-021-00984-y

[13] Maghdid, H. S., Asaad, A. T., Ghafoor, K. Z., Sadiq, A. S., Mirjalili, S., & Khan, M. K. (2021, April). Diagnosing COVID-19 pneumonia from X-ray and CT images using deep learning and transfer learning algorithms. In Multimodal Image Exploitation and Learning 2021 (Vol. 11734, p. 117340E). International Society for Optics and Photonics. https://doi.org/10.1117/12.2588672

[14] Wang, S., Kang, B., Ma, J., Zeng, X., Xiao, M., Guo, J., & Xu, B. (2021). A deep learning algorithm using CT images to screen for Corona Virus Disease (COVID-19). European radiology, 1-9. https://doi.org/10.1101/2020.02.14.20023028

[15] Li, L., Qin, L., Xu, Z., Yin, Y., Wang, X., Kong, B., ... & Xia, J. (2020). Using artificial intelligence to detect COVID-19 and community-acquired pneumonia based on pulmonary CT: evaluation of the diagnostic accuracy. Radiology, 296(2), E65-E71. https://doi.org/10.1148/radiol.2020200905

[16] Song, Y., Zheng, S., Li, L., Zhang, X., Zhang, X., Huang, Z., & Yang, Y. (2021). Deep learning enables accurate diagnosis of novel coronavirus (COVID-19) with CT images. IEEE/ACM Transactions on Computational Biology and Bioinformatics. https://doi.org/10.1109/TCBB.2021.3065361

Dataset [17] GitHub. COVID-CT dataset, https://github.com/UCSD-AI4H/COVID-CT. Accessed 07 June 2021

[18] Iandola, F. N., Han, S., Moskewicz, M. W., Ashraf, K., Dally, W. J., & Keutzer, K. (2016). SqueezeNet: AlexNet-level accuracy with 50x fewer parameters and< 0.5 MB model size. arXiv preprint arXiv:1602.07360.

[19] Ma, N., Zhang, X., Zheng, H. T., & Sun, J. (2018). Shufflenet v2: Practical guidelines for efficient cnn architecture design. In Proceedings of the European conference on computer vision (ECCV) (pp. 116-131). arXiv: arXiv:1807.11164

[20] Sandler, M., Howard, A., Zhu, M., Zhmoginov, A., & Chen, L. C. (2018). Mobilenetv2: Inverted residuals and linear bottlenecks. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 4510-4520). arXiv:1807.11164v1

[21] He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 770-778).

[22] MathWorks, Inc. (2021b). Deep Learning Toolbox: User's Guide (r2021b)

[23] Alshazly, H., Linse, C., Barth, E., & Martinetz, T. (2021). Explainable covid-19 detection using chest ct scans and deep learning. Sensors, 21(2), 455. https://doi.org/10.3390/s21020455

[24] Chaddad, A., Hassan, L., & Desrosiers, C. (2021). Deep CNN models for predicting COVID-19 in CT and x-ray images. Journal of medical imaging (Bellingham, Wash.), 8(Suppl 1), 014502. https://doi.org/10.1117/1.JMI.8.S1.014502

[25] Gifani P, Shalbaf, A., & Vafaeezadeh, M. (2021). Automated detection of COVID-19 using ensemble of transfer learning with deep convolutional neural network based on CT scans. International journal of computer assisted radiology and surgery, 16(1), 115-123. https://doi.org/10.1007/s11548-020-02286-w

[26] Saqib, M.; Anwar, S.; Anwar, A.; Petersson, L.; Sharma, N.; Blumenstein, M. COVID19 Detection from Radiographs: Is Deep Learning Able to Handle the Crisis?. Preprints 2020, 2020060189

[27] Martinez, A. R. (2020). Classification of covid-19 in ct scans using multi-source transfer learning. arXiv preprint arXiv:2009.10474.

[28] Islam, M. R., & Matin, A. (2020, December). Detection of COVID 19 from CT Image by The Novel LeNet-5 CNN Architecture. In 2020 23rd International Conference on Computer and Information Technology (ICCIT) (pp. 1-5). IEEE. https://doi.org/10.1109/ICCIT51783.2020.9392723