Deep Learning Model for Diagnosis of Corona Virus Disease from CT Images

Mehmet Akif Cifci

Abstract—Purpose: SARS-COV-2, a severe acute respiratory syndrome, has caused more than 1 million to be infected worldwide. Corona Virus Disease, known as COVID-19, has cases that are worldwide and widespread. What is worse, this number continues to increase. Early diagnosis of COVID-19 and finding high-risk patients with a worse prognosis for early prevention is vital. It is essential to screen as many as suspect cases for appropriate quarantine and treatment measures to control the spread of the disease. The viral test based on samples taken from the lower respiratory tract is the critical standard of diagnosis. However, the availability and quality of laboratory tests in the infected area may cause inaccurate results, false positive.
Methods: In this study, a Deep Learning (DL) method for COVID-19 diagnostic and prognostic analysis using Computed Tomography (CT) scans is studied. Based on the COVID-19 CT images, it is aimed to diagnose COVID- 19 at an early stage. Thus, it may take place before a clinical diagnosis before pathogenic testing.
Results: For the testing probability of the disease, 5800 CT images were taken from Kaggle web. 4640 (80%) CT images are used as the training step, while 1160 (20%) images are benefitted for the testing step. AlexNet has achieved an overall accuracy of 94. 74%, with 87. 37% sensitivity and 87. 45% as specificity while Inception-V4 has an overall accuracy of 84. 14%, with 87. 09% sensitivity and 84. 14% as specificity. These results show the high value of using Deep learning for early diagnosis of COVID-19. Deep learning is used as a beneficial tool for fast screening COVID-19. In this study, it is benefitted to find potential high-risk patients.

Index Terms— Coronavirus, COVID-19, deep learning, machine learning, CT images

1 Introduction

Deep Learning (DL) methods can be used in biomedical sciences and to help with the early predictions to identify and classify the corona virus disease [1]. Screening CT dataset to diagnose COVID-19, SARS-COV-2, the new corona virus disease which first appeared in Wuhan, China in December 2019 [2] and so far caused 64,384 deaths, as of April 5, approximately more than one million cases confirmed worldwide, with many more requiring to be tested [3]. However, it is not possible to check and cure all infected patients for a large number of suspicious and asymptomatic infected patients.

Due to the high infection rate, a fast diagnosis using AI methods becomes inevitable. Accurate and rapid diagnosis of COVID-19 can help isolate infected patients to slow the spread of the disease [4]. On the other hand, insufficient medical resources in the epidemic field have become a significant challenge. Thus, it is vital to identify infected individuals as soon as possible to take under quarantine and apply treatment procedures. Diagnosis of COVID-19 tests is so far done with clinical symptoms, epidemiological history and positive CT images and positive pathogenic test [5].

Here it is hoped to take advantage of the emerging DL methods, which enables analysis of the CT images by applying appropriate algorithms for early prediction of the corona virus disease. About 5800 COVID-19 CT scans were obtained from the Kaggle website [6]. Before applying DL methods, the images were preprocessed. Such filters like Gaussian Blur, Otsu threshold, Splitting the Image, Flipping the Image, Histogram Features [7]. Also, a Convolutional Neural Network (CNN or ConvNet), a class of deep neural networks, is used to process the CT images to classify or detect the corona virus disease [8].

The article is presented as follows. Section 2 discusses the literature review, the studies done on COVID-19 using Machine Learning (ML) methods. Section 3 describes the proposed technique for early diagnosis of COVID-19 from CT image datasets with DL model and five image filters. Section 4 is about the proposed architecture in which DL methods are used. Section 5 presents the experimental results and evaluation. Section 6 shows the discussion on the architecture. Finally, Section 7 shows the results of the study.

• *Mehmet Akif CIFCI is currently pursuing Ph. D. degree program in artificial Intellgence in computer engineering in IAU, Turkey, in addition to being a computer engineering, he serves as an academician, as a teacher/mentor. Beside being a member of IEEE he generally volunteer works charity business, PH-905320664035. E-mail: wwwakif@msn. com*

2 Literature Review

In [9], the authors developed a conventional statistical and ML tool that is applied for feature extraction from CT images COVID-19 infection regions through their finding that gives many false-negative results. While [10] showed that in the early stage of identification of the disease, the study has a relatively low positive rate regarding evaluating COVID-19. In [11], the research is aimed to establish a model of deep learning-based quantitative CT images in which the authors focus on the logistic regression model for predicting the severity of COVID-19. [12] is about using Lasso regression screening and multivariate logistic regression to predict COVID-19. The authors take such variables (age, Red Blood Cell etc.) into account. In [13], the authors study a fully automatic DL system that provides a convenient method for COVID-19 diagnostic. To let DL system mine lung features automatically, they benefitted a two-step transfer learning strategy. [13] studies on patients whom they put into groups based on the interval between symptom onset and the first CT scan. Their finding is COVID-19 pneumonia manifests with chest CT imaging abnormalities, even in asymptomatic patients[14].

3 Materials and Methods

DL enables computational models consisting of multiple processing layers to learn [15] representations of data with various levels of abstraction. These methods have significantly improved the latest technology in many other areas such as speech recognition, visual object recognition, object detection, and drug discovery, and genomics. DL technique generally consists of three main components [16]. These are listed as the convolution layer, the common layer, and the output layer. By bringing these layers together, a multi-layered structure is created, and the pattern data of the input image gradually lose size [17]. At the last point, the attributes of the input image are mapped as the output layer for classification. The proposed approach for the detection of COVID-19 from CT images, preprocessing. The purpose of size reduction is to reduce the calculation time and cost in the classification method [18]. Linear Discriminant Analysis (LDA) was used for size reduction [19]. Maximum features used for classification increase computing time and storage memory. At the classification stage, CT images are classified as normal or infected based on DL method used which discovers the complex structure in large datasets using the backpropagation [20] algorithm to indicate how a machine should change the internal parameters used to calculate the representation on each layer from the representation on the previous layer. In DL model training, testing, validation phases will be focused on [21].

The classifier is trained with the selected features of the training data. On the other hand, in the testing phase, the results of the classification procedure indicate whether the images have COVID-19. The current working architecture is seen in Fig. 1.

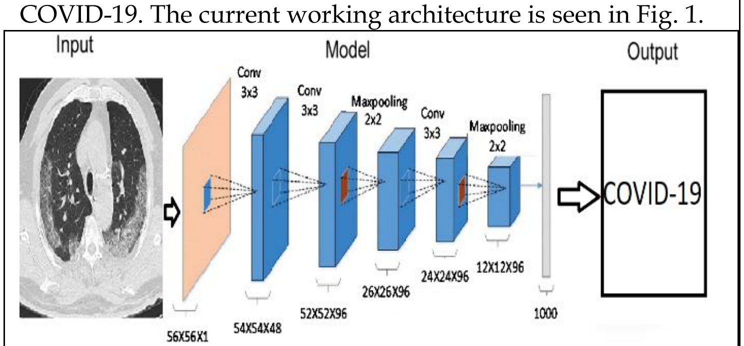

Fig. 1. Deep Learning Architecture.

On Fig. 1 as seen first the input CT images are taken into the system then it is applied Conv within hidden layers, finetuning and there comes the output. For the system no region of interest has been provided for suspected lesions in the images [22]. After training, CT images are diagnosed with DL as having COVID-19 or normal.

3.1 Image Data Set

The CT images data set used in this study was obtained from a source (KAGGLE) published on the Internet [23]. Therefore, an Ethics Committee approval or informed consent form is not required. CT scans are in Digital Imaging and Communications in Medicine (DICOM) format, a special format for CT images, which is the standard for communication and management of medical imaging information and related data. The CT images are as on Fig. 2

Fig. 2. Different CT images samples

It is aimed to diagnose COVID-19 form CT images by using CNN shown in Fig. 1, for which a set of CT-images of COVID-19 from the kaggle. com benchmark web of dataset science, as shown in below Fig. 2 was tested, to perform the accuracy of early-screen diagnosis.

3.2 Image Processing

Negative Image: CT images are images with a grayscale value. The grayscale image is an image where each pixel has only one representative amount of light, and each pixel is 8 bits (0-255) [24]. The maximum number of colors that can be displayed in gray images at any time is 256. Lung CT images are not characteristically clear, so for better performance in image processing, it is necessary to convert the grayscale image to a negative image.

$$PixelRate[x, y] = 255 - Pixelrate[x, y] \qquad (1)$$

where x represents the number of columns, and y represents the number of rows. The CT grayscale image shown in Fig. 3 is negative.

Fig. 3. Negative of the CT image.

3.2.1 Gaussian Blur

Gaussian blur [25] is applied to each CT image to reduce all noise of the CT images (Fig. 4). After doing this operation, CT images will have the same features.

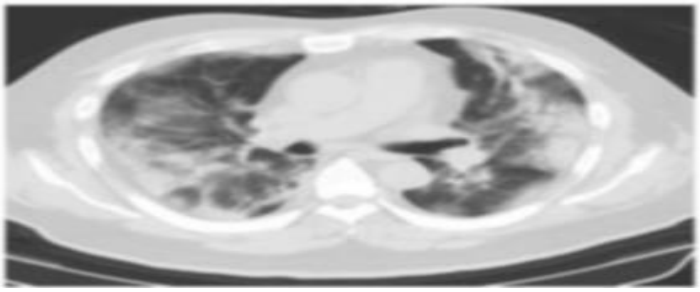

Fig. 4. Gaussian blur application to CT images.

When blurring affects CT images, it reduces the visualization and visibility of small components in the image. For this reason, Gaussian blur is essential to restore the intact form of the image from its distorted version and give the image a sharper look [7].

$$G(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{x^2+y^2}{2\sigma^2}} \quad (2)$$

$$Sigma(\sigma) = 0.3x\left((kernelsize - 1)x0.5 - 1\right) + 0.8$$

In the formula 2, x represents the number of columns, and y represents the number of rows in the core. The 7 × 7 Core is used for this function.

3.2.2 Otsu Threshold

The Otsu method is a general threshold technique [26]. Uses the histogram of the image for threshold search. Maximizes the "among the class variance" value of partitioned classes. Otsu is achieved by minimizing or maximizing "variance. "

Otsu is a threshold method applied to every image. Otsu's algorithm finds a threshold value (t) that minimizes the weighted class variance with this relationship [27].

$$a_\omega^2(t) = q_1(t)a_1^2(t) + q_2(t)a_2^2(t) \quad (3)$$

Here:

$$q_1(t) = \sum p(i)$$

$$q_2(t) = \sum p(i)$$

As seen in the formula 3, P (i) is the probability of each pixel value. The threshold converts images into a simpler form of an image and the perception of the lung region infected (Fig. 5).

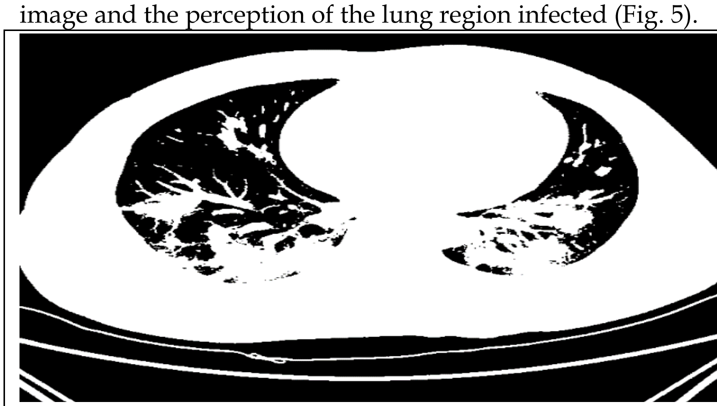

Fig. 5. Otsu threshold applied to the CT image.

3.2.3 Splitting the Image

The human lung is symmetrical. The center of the starting point is selected, and with this point, it divides the image of the right and left lungs. The image is cropped at that point and converts the left and right images into two specific images. Lung CT images are divided into two for better results as seen in Fig. 5 [28].

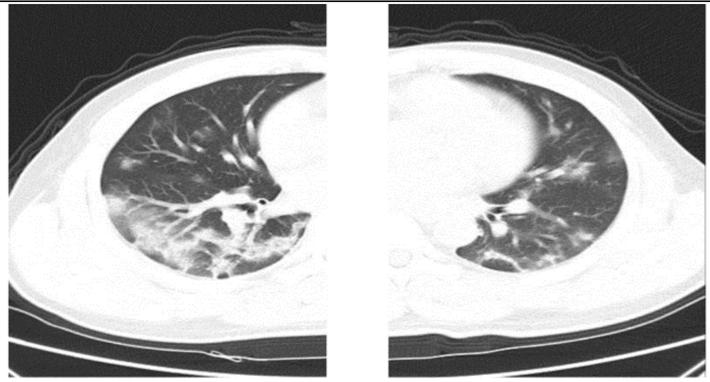

Fig. 6. Splitting the image

3.2.4 Flipping the Image

After the CT images are divided, they become two parts right and left to make the model to understand the image better (Fig. 7). The equation for this process is as follows:

$PixelRate[x, y] = PR[x, column - y - 1]$ (4)

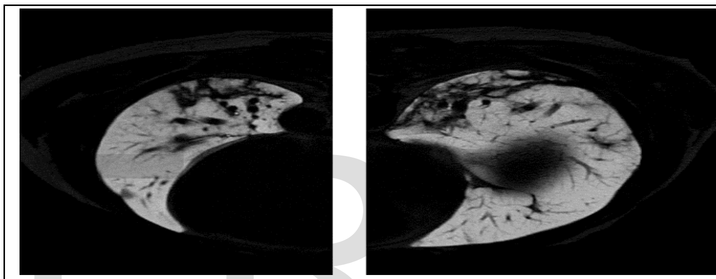

Fig. 7. Flipping the Image.

3.2.5 Histogram Features

In the histogram features, the image is displayed in pixels. The histogram shows the number of pixels in each power value in the image. Conversion of the image histogram to power values is done by pairing it with a predetermined histogram (Fig. 8).

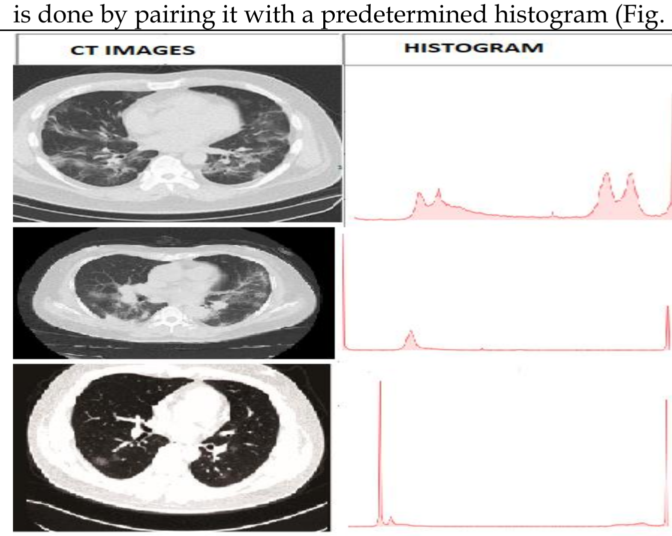

Fig. 8. Histogram and preprocessed images.

From the input image, the total gray level range is evaluated by the histogram method. There are 256 gray levels, ranging from 0 to 255. It has some common features such as variance, mean, skewness, kurtosis, and standard deviation.

4 THE PROPOSED ARCHITECTURE

The proposed DL system is essential in using CNN architecture. In this DL system, two DL networks are involved: Inception-V4 and AlexNet, the proposed novel is basically for corona virus diagnostic and prognostic analysis [29]. DL is a family of hierarchical neural networks that aim at learning the abstract mapping between raw data to the desired outcome [30]. The computational units in DL model are defined as layers, and they are integrated to simulate the inference process of the human brain. The main computational formulas are convolution, pooling, activation, and batch normalization, as defined in the supplementary.

4.1 Metrics used in health check systems for evaluation

Different performance metrics are often used to investigate the performance of different models, such as precision, accuracy, Sensitivity (Table 1).

TABLE 1.
METRICS USED IN HEALTH

1) Sensitivity: It is the ability of a test to identify those with the disease correctly

$$\text{Sensitivity} = \frac{TP}{TP+FN} \quad (5)$$

2) Specificity: It refers to how well a test identifies patients who do not have a disease

$$\text{Specificity} = \frac{TN}{TN+FP} \quad (6)$$

3) Accuracy: can be calculated by dividing the number of accurate estimates by the total number of all calculations.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (7)$$

4.2 AlexNet

AlexNet is one of the most famous of CNN architectures. In 2012 AlexNet accomplished state-of-the-art recognition accuracy against all the traditional ML and all other computer approaches. It was a noteworthy breakthrough in the field of ML for image recognition and classification process and it is the key point in history where interest in DL has started to increase [31].

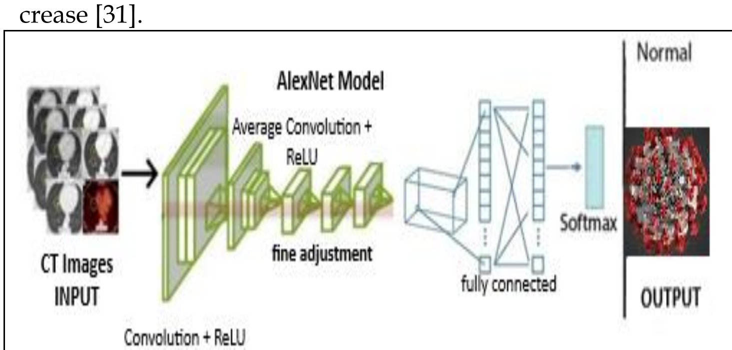

Fig. 9. Flow chart of AlexNet method.

The architecture of AlexNet is seen in Fig. 9. The first convolutional layer performs convolution and maximum pooling with Local Response Normalization using 96 different receiving filters of 11 × 11 size. Maximum pooling is done with 3 × 3 filters with step size 2. The same operations are performed on the second layer with a 5 × 5 filter. 3 × 3 filters with 384, 384 and 296 feature maps are used in the third, fourth, and fifth convolutional layers, respectively. Two fully connected layers are used with dropout followed by a Softmax layer at the end [32]. .

As seen in Fig. 9, in the first step, the data set is taken into AlexNet to be analyzed. I. e. to the trained network. The basic architecture of the proposed system is created in this way. Besides, L2-norm regularization has been adopted to prevent overfitting and improve generalization of results [33].

To train the network, the stochastic gradient estimation method with 0,9 acceleration was used [34]. About 80% of the data set were used for training, the remaining 20% for testing. To determine the number of cycles, error-free verification was performed at the end of each iteration.

Table 2.
ALEXNET TEST RESULTS

Accuracy	Sensitivity	Specificity	loss
86. 8	90. 5	88. 3	0. 3879
94. 0	90. 6	87. 9	0. 1692
95. 5	84. 7	87. 5	0. 1451
95. 2	86. 8	86. 1	0. 1711
95. 3	84. 9	86. 8	0. 1139
96. 4	89. 0	87. 0	0. 1212
96. 8	87. 5	88. 3	0. 1458
94. 1	86. 1	87. 2	0. 1193
96. 7	86. 7	87. 9	0. 1128
96. 6	86. 9	87. 5	0. 1052

By changing the loss function, it is aimed to find the best accuracy rate.

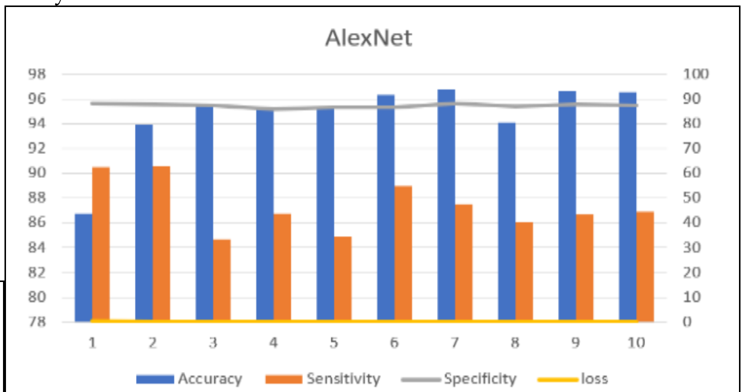

Fig. 10. AlexNet showing results.

4.3 Inception-V4:

In computer vision, Inception is a striking deep neural network architecture [35]. The startup algorithm performs much better for built-in or mobile computing devices. The way to increase accuracy in deep CNN is to increase the level of work and the number of units in average sizes at each level. Initially, 1 × 1, 3 × 3, 5 × 5 convolution filter and 3 × 3 maximum affinity filter is used. The maximum bonding process in the convolution layer is very effective. The initial is optimal sparse architecture and 3 ~ 10 × faster than other architecture [36].

TABLE 3.
INCEPTION-V4 TEST RESULTS

Sensitivity	Specificity	Accuracy	loss
88. 23	90. 19	92. 15	0. 4871
90. 09	63. 91	77. 83	0. 5673
81. 79	79. 45	88. 11	0. 3854
79. 75	73. 15	66. 55	0. 4612
91. 53	92. 78	94. 03	0. 2533
90. 17	90. 22	90. 28	0. 5274
88. 80	87. 66	86. 53	0. 2462
87. 44	85. 11	82. 77	0. 4191
86. 07	82. 55	79. 02	0. 2412

The overall improvement in the used Inception-V4 model produces an average, like 81. 14%. The Fig. below shows it summarize for all the test results in Fig. 11.

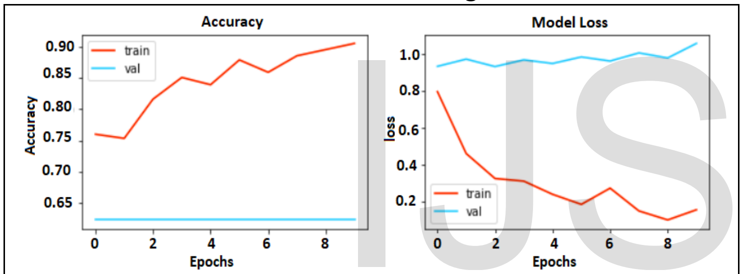

Fig. 11. Inception-V4.

5 EXPERIMENTAL RESULTS

In the study to diagnose COVID-19 at an early stage to isolate those who carry the disease can help to decrease the speed of contagion. Two different methods are used and compared for the AlexNet method, the accuracy average is 94. 74%, and the results are as shown in Table 2.

In contrast, for Inception-V4, the result of the accuracy average is 81. 14%, and the results are as shown in Table 3. According to the proposed model presented in this study, these comparisons reduced the false-negative rate and showed a relatively high overall accuracy with more accurate results. The best result is displayed with the AlexNet method [23]. What is more important, the CT scans are applied five different filters, which help with the results of optimizing DL model to select the best sensitive features from CT images.

6 DISCUSSION

In this study, a DL method is proposed using a raw chest CT image dataset to assist in the diagnosis and prognostic analysis of COVID-19 [37]. CNN strategy is benefitted to generate lung features automatically. First, 5800, CT images were collected from Kaggle Web. The CT images were taken into image preprocessed. Thanks to the training in this CT image data set, DL method learns to classify and diagnose COVID-19 at a higher rate accuracy.

7 RESULT

In this paper, DL architecture for early diagnosis of COVID-19 by using a benchmark CT-Images dataset is proposed. The proposed model shows better results when two methods are taken into consideration. DL is much better than the traditional classification approaches for image classification [5], [38] process, and effectively reduced the false-negative rate with high accuracy, especially when using the AlexNet method. However, it is an old method that still finishes the test with 94. 74% compared to Inception-V4 with and accuracy 81. 14%, which is considerably less than the previous state-of-the-art result. The results of the proposed model have a high accuracy of COVID-19 CT images [39].

DL method to be used to diagnose COVID-19 can efficiently and accurately calculate the infection of 5800 patients through simple and easily collected CT images, which in the near future can be applied to laboratory CT images as well. The architecture can be used to screen a large number of suspected people's CT data sets to save people's lives and to save limited medical resources [37]. Optimize the diagnosis process, and it can constantly learn, adapt, and upgrade can be improved soon as future work.

References

[1] [1] S. Wang et al. , "A Fully Automatic Deep Learning System for COVID-19 Diagnostic and Prognostic Analysis," medRxiv, p. 2020. 03. 24. 20042317, 2020, doi: 10. 1101/2020. 03. 24. 20042317.

[2] [2] Z. Ling et al. , "Asymptomatic SARS-CoV-2 infected patients with persistent negative CT findings," Eur. J. Radiol. , 2020, doi: 10. 1016/j. ejrad. 2020. 108956.

[3] [3] C. Anastassopoulou, L. Russo, A. Tsakris, and C. Siettos, "Data-based analysis, modelling and forecasting of the COVID-19 outbreak," PLoS One, vol. 15, no. 3, p. e0230405, 2020, doi: 10. 1371/journal. pone. 0230405.

[4] [4] R. Magar, P. Yadav, and A. B. Farimani, "Potential Neutralizing Antibodies Discovered for Novel Corona Virus Using Machine Learning," no. Md, 2020, [Online]. Available: http://arxiv. org/abs/2003. 08447.

[5] [5] A. A. Farid, G. I. Selim, H. Awad, and A. Khater, "A Novel Approach of CT Images Feature Analysis and Prediction to Screen for Corona Virus Disease (COVID-19)," Int. J. Sci. Eng. Res. , vol. 11, no. 3, pp. 1–9, 2020, [Online]. Available: http://www. ijser. org.

[6] [6] D. S. Kermany et al. , "Identifying Medical Diagnoses and Treatable Diseases by Image-Based Deep Learning," Cell, 2018, doi: 10. 1016/j. cell. 2018. 02. 010.

[7] [7] P. Gupta and A. K. Malhi, "Using deep learning to enhance head and neck cancer diagnosis and classification," in 2018 IEEE International Conference on System, Computation, Automation and Networking, ICSCA 2018, 2018, doi: 10. 1109/ICSCAN. 2018. 8541142.

[8] [8] J. L. Causey et al. , "Lung cancer screening with low-dose CT scans using a deep learning approach," 2019, [Online]. Available: http://arxiv. org/abs/1906. 00240.

[9] [9] T. Ai 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, doi: 10. 1148/radiol. 2020200642.

[10] [10] 6(1). http://doi. org/10. 1186/s13613-015-0104-6 Deye, N. , Vincent, F. , Michel, P. , Ehrmann, S. , Da Silva, D. , Piagnerelli, M. , … Laterre, P. -F. (2016). Changes in cardiac arrest patientsâ€TM temperature management after the 2013 â€œTTMâ€□ trial: Results from an international survey. Annals of Intensive et al. , "Community outreach: Educating the well child and easing transition after treatment

for the oncology patient," Pediatr. Blood Cancer, 2015, doi: 10. 1002/pbc. 25715.

[11] [11] W. Shi et al. , "The Lancet Infectious Diseases Deep Learning-Based Quantitative Computed Tomography model in Predicting the Severity of COVID-19 : A Retrospective Study in 196 Patients," 2020.

[12] [12] Z. Meng et al. , "Development and utilization of an intelligent application for aiding COVID-19 diagnosis," medRxiv, no. 37, p. 2020. 03. 18. 20035816, 2020, doi: 10. 1101/2020. 03. 18. 20035816.

[13] [13] S. Wang et al. , "A Fully Automatic Deep Learning System for COVID-19 Diagnostic and Prognostic Analysis," medRxiv, 2020, doi: 10. 1101/2020. 03. 24. 20042317.

[14] [14] K. C. Santosh, "AI-Driven Tools for Coronavirus Outbreak: Need of Active Learning and Cross-Population Train/Test Models on Multitudinal/Multimodal Data. ," J. Med. Syst. , 2020, doi: 10. 1007/s10916-020-01562-1.

[15] [15] Z. Zhong et al. , "3D fully convolutional networks for co-segmentation of tumors on PET-CT images," Proc. - Int. Symp. Biomed. Imaging, vol. 2018-April, no. Isbi, pp. 228–231, 2018, doi: 10. 1109/ISBI. 2018. 8363561.

[16] [16] N. Buduma, Fundamentals of Deep Learning. 2015.

[17] [17] W. Alakwaa, M. Nassef, and A. Badr, "Lung cancer detection and classification with 3D convolutional neural network (3D-CNN)," Int. J. Biol. Biomed. Eng. , vol. 11, no. November, pp. 66–73, 2017, doi: 10. 14569/ijacsa. 2017. 080853.

[18] [18] J. Liang, E. Meyerson, B. Hodjat, D. Fink, K. Mutch, and R. Miikkulainen, "Evolutionary neural automl for deep learning," in GECCO 2019 - Proceedings of the 2019 Genetic and Evolutionary Computation Conference, 2019, doi: 10. 1145/3321707. 3321721.

[19] [19] Y. H. , L. C. , S. X. , Z. C. , Z. T. , and Z. K. , "Lung nodules detection system using support vector machine classifier combined linear discriminant analysis-based feature selection with rule-based feature pruning," J. Med. Imaging Heal. Informatics, 2019, doi: 10. 1166/jmihi. 2019. 2596 LK - http://elinks. library. upenn. edu/sfx_local?sid=EMBASE&issn=21567026&id=doi:10. 1166%2Fjmihi. 2019. 2596&atitle=Lung+nodules+detection+system+using+support+vector+machine+classifier+combined+linear+discriminant+analysis-based+feature+selection+with+rule-based+feature+pruning&stitle=J. +Med. +Imaging+Health+Informatics&title=Journal+of+Medical+Imaging+and+Health+Informatics&volume=9&issue=3&spage=408&epage=417&aulast=Yuan&aufirst=Haiying&auinit=H. &aufull=Yuan+H. &coden=&isbn.

[20] [20] J. Flenner, B. Hunter, J. Flenner, and B. Hunter, "A Deep Non-Negative Matrix Factorization Neural Network," Submitted, 2016.

[21] [21] G. Huang, Z. Liu, L. Van Der Maaten, and K. Q. Weinberger, "Densely connected convolutional networks," Proc. - 30th IEEE Conf. Comput. Vis. Pattern Recognition, CVPR 2017, vol. 2017-Janua, no. July, pp. 2261–2269, 2017, doi: 10. 1109/CVPR. 2017. 243.

[22] [22] L. T. , Z. W. , Z. Q. , X. L. , Z. L. , and C. Y. , "Deep learning-based dual-energy computed tomography imaging," Int. J. Comput. Assist. Radiol. Surg. , 2019, doi: 10. 1007/s11548-019-01969-3 LK - http://elinks. library. upenn. edu/sfx_local?sid=EMBASE&issn=18616429&id=doi:10. 1007%2Fs11548-019-01969-3&atitle=Deep+learning-based+dual-energy+computed+tomography+imaging&stitle=Int. +J. +Comput. +Assisted+Radiol. +Surg. &title=International+Journal+of+Computer+Assisted+Radiology+and+Surgery&volume=14&issue=&spage=S98&epage=S99&aulast=Lv &aufirst=T. &auinit=T. &aufull=Lv+T. &coden=&isbn=&pages=S98-S99&date=2019&auinit1=T&auinitm=.

[23] [23] J. Chen et al. , "Deep learning-based model for detecting 2019 novel coronavirus pneumonia on high-resolution computed tomography: a prospective study," medRxiv, 2020, doi: 10. 1101/2020. 02. 25. 20021568.

[24] [24] N. Zeng, H. Qiu, Z. Wang, W. Liu, H. Zhang, and Y. Li, "A new switching-delayed-PSO-based optimized SVM algorithm for diagnosis of Alzheimer's disease," Neurocomputing, 2018, doi: 10. 1016/j. neucom. 2018. 09. 001.

[25] [25] C. E. Rasmussen and C. K. I. Williams, Gaussian Processes for Machine Learning. 2018.

[26] [26] R. Helen, N. Kamaraj, K. Selvi, and V. Raja Raman, "Segmentation of pulmonary parenchyma in CT lung images based on 2D Otsu optimized by PSO," in 2011 International Conference on Emerging Trends in Electrical and Computer Technology, ICETECT 2011, 2011, doi: 10. 1109/ICETECT. 2011. 5760176.

[27] [27] J. Bhatt, M. Joshi, and M. Sharma, "Early detection of lung cancer from CT images: nodule segmentation and classification using deep learning," 2018, doi: 10. 1117/12. 2309530.

[28] [28] P. Kavitha and S. Prabakaran, "A novel hybrid segmentation method with particle swarm optimization and fuzzy c-mean based on partitioning the image for detecting lung cancer," Int. J. Eng. Adv. Technol. , vol. 8, no. 5, pp. 1223–1227, 2019, doi: 10. 20944/preprints201906. 0195. v1.

[29] [29] M. S. Rahman, P. C. Shill, and Z. Homayra, "A New Method for Lung Nodule Detection Using Deep Neural Networks for CT Images," 2nd Int. Conf. Electr. Comput. Commun. Eng. ECCE 2019, pp. 1–6, 2019, doi: 10. 1109/ECACE. 2019. 8679439.

[30] [30] K. K. To et al. , "Articles Temporal profiles of viral load in posterior oropharyngeal saliva samples and serum antibody responses during infection by SARS-CoV-2 : an observational cohort study," Lancet Infect. Dis. , 2020, doi: 10. 1016/S1473-3099(20)30196-1.

[31] [31] L. V. , K. V. , T. A. , S. E. , G. A. , and R. A. , "Detecting lung lesions based on Deep Learning for constructing medically-meaningful TB descriptors," Int. J. Comput. Assist. Radiol. Surg. , 2019, doi: 10. 1007/s11548-019-01969-3 LK - http://elinks. library. upenn. edu/sfx_local?sid=EMBASE&issn=18616429&id=doi:10. 1007%2Fs11548-019-01969-3&atitle=Detecting+lung+lesions+based+on+Deep+Learning+for+constructing+medically-meaningful+TB+descriptors&stitle=Int. +J. +Comput. +Assisted+Radiol. +Surg. &title=International+Journal+of+Computer+Assisted+Radiology+and+Surgery&volume=14&issue=&spage=S75&epage=&aulast=Liauchuk&aufirst=V. &auinit=V. &aufull=Liauchuk+V. &coden=&isbn=&pages=S75-&date=2019&auinit1=V&auinitm.

[32] [32] Z. Allen-Zhu, Y. Li, and Z. Song, "A convergence theory for deep learning via over-parameterization," in 36th International Conference on Machine Learning, ICML 2019, 2019.

[33] [33] S. T. and T. A. , "Comparison of diagnostic performance of deep convolutional neural network using fine-tuning and feature extraction on dopamine transporter single photon emission tomography images," J. Nucl. Med. , 2019.

[34] [34] A. M. DSouza, A. Z. Abidin, and A. Wismüller, "Automated identification of thoracic pathology from chest radiographs with enhanced training pipeline," 2019, doi: 10. 1117/12. 2512600.

[35] [35] R. V. M. Da Nóbrega, S. A. Peixoto, S. P. P. Da Silva, and P. P. R. Filho, "Lung Nodule Classification via Deep Transfer Learning in CT Lung Images," in Proceedings - IEEE Symposium on Computer-Based Medical Systems, 2018, doi: 10. 1109/CBMS. 2018. 00050.

[36] [36] H. Park and C. Monahan, "Genetic Deep Learning for Lung Cancer Screening," 2019, [Online]. Available: http://arxiv. org/abs/1907. 11849.

[37] [37] C. Zheng et al. , "Deep Learning-based Detection for COVID-19 from Chest CT using Weak Label," medRxiv, 2020, doi: 10. 1101/2020. 03. 12. 20027185.

[38] [38] S. Cui, Y. Luo, H. H. Tseng, R. K. Ten Haken, and I. El Naqa, "Combining handcrafted features with latent variables in machine learning for prediction of radiation-induced lung damage," Med. Phys. , 2019, doi: 10. 1002/mp. 13497.

[39] [39] A. -T. Ton, F. Gentile, M. Hsing, F. Ban, and A. Cherkasov, "Rapid Identification of Potential Inhibitors of SARS-CoV-2 Main Protease by Deep Docking of 1. 3 Billion Compounds," Mol. Inform. , 2020, doi: 10. 1002/minf. 202000028.