Deep Convolutional Neural Networks for COVID-19 detection from CT scans: A survey

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***Abstract*—Since the Coronavirus outbreak in December of 2019, people have put a lot of effort into its early diagnosis by assessing signs and symptoms obtained from various studies. To this goal, deep learning models are trained to detect the presence of COVID-19 from three most commonly used lung-imaging modes: X-Ray, Ultrasound, and Computed Tomography (CT) scan. This survey compares current Deep Convolutional Neural Networks approaches for the classification of CT scans considering datasets, neural network architectures, and evaluation metrics. It gives new researchers in this field an excellent starting point providing currently most popular and prosperous CNN architectures and large available diverse datasets.**

I. Introduction

Coronavirus disease (COVID-19) caused by severe acute respiratory syndrome continues to have a significant influence on the world. Since the outbreak, the disease has spread to almost every country. As of February 17th, 2021, there are more than 2.4 million deaths and over 108 million confirmed cases of infection based on the World Health Organization statistics [1]. Even though the mortality rate of COVID-19 is less than that of severe acute respiratory syndrome (SARS) and the Middle East respiratory syndrome (MERS) its highly infectious nature makes the number of cases continuously rise [2]. Governments around the world have proposed different policies to mitigate the effects of the pandemic and save patients and health systems. Scientists quickly adapted and contributed significantly to this cause by searching for new technology to screen infected patients, make an early diagnosis, control the spread of the virus, develop a vaccine, trace contacts of infected patients, etc. It is evident that Artificial Intelligence (AI) and Machine Learning (ML) can contribute a lot to the fight against coronavirus. Moreover, recent studies show that ML and AI are promising technologies to provide clinical decision support for medical workers [3].

In the absence of vaccines or specific drugs for COVID-19, fast and effective screening tools to identify infected patients are essential. Early detection of disease will ensure the patient's timely isolation and treatment and help prevent the further spread of the virus. Currently, Reverse transcription polymerase chain reaction (RT-PCR) testing is the primary means of virus detection. However, this kind of testing has a variable sensitivity depending on sampling method and time since the onset of symptoms. The process is time-consuming, manual, and requires bimolecular facilities which in times of high demand can lead to delays in obtaining test results [4]. An alternative approach is the usage of radiological imaging (computed tomography (CT), X-Ray, Ultrasound, etc.). A chest CT is a conventional, reliable, and rapid method that produces a precise image of a patient's chest. CT images provide more details than standard X-Ray. Compared to the other imaging techniques such as X-ray, CT provides lower false-positive rates [4]. Compared to RT-PCR, chest CT has a high sensitivity for the diagnosis of COVID-19 and may be considered as a primary tool for disease detection in epidemic areas.

Healthcare experts and radiologists can use radiology images to detect COVID-19. However, their tasks are manual and time-consuming, which is a problem during the pandemic when they are required to examine a lot of cases. To support them in improving their diagnosis performance, AI methods, especially deep learning, can be used to process and analyze medical imaging data. Convolutional Neural Networks (CNNs) have proven to be highly effective in a vast range of medical image classification [5, 6]. Some of the most commonly used architectures are: AlexNet [7], ResNet [8], VGG [9], Xception [10], DenseNet, [11], Inception [12], etc.

There are surveys describing different artificial intelligence applications relevant to the Covid-19 crisis. Those applications include Internet of things (IoT), Covid-19 modeling, Text Mining and Natural Language Processing for Covid-19, Image processing with deep learning, [13] Covid-19 prediction and forecasting, and contact tracking [14]. In [15] authors review computer vision efforts and methods to combat the COVID-19 pandemic.

This survey offers a detailed analysis of existing Deep Convolutional Neural Networks for COVID-19 lung CT scans classification and an overview of publicly available CT scan datasets. It gives a better understanding of currently available datasets, baseline efforts, new trends, and innovative ideas about CNN architectures providing an excellent starting point for new researchers in this field.

The rest of this paper is organized as follows. Section 2 gives an overview of several representative studies on CT-based CNN architectures. Section 3 presents a list of publicly available CT scans datasets relevant for COVID-19 diagnosis. In section 4 remarks are made about the most promising network architectures, challenges when it comes to diversity and size of datasets, and practical implementation of CNN. A short conclusion and suggestions for future work are given in the last section.

II. NETWORK ARCHITECTURE ANALYSIS

Many papers are dealing with the application of computer vision for COVID-19 diagnosis using radiology images. Some recent, representative works that classify lung CT scans based on the presence of the coronavirus using CNNs are summarized in Table I for comparison. It must be noted that they have utilized a diverse number of images and datasets and used different metrics to measure performance. These circumstances make their comparison more difficult. The most frequently used metrics are Accuracy (percentage of correct classifications, ACC), Precision or Positive Predictive Value (percentage of correct positive classifications, PPV), Sensitivity or True Positive Rate (percentage of actual positives classified correctly, TPR), F1 score (harmonic mean of the previous two), Specificity of True Negative Rate (percentage of actual negatives classified correctly, TNR), and Area Under the ROC curve (AUC).

Transfer learning is a popular method for the COVID-19 diagnosis problem. It is useful when there is not enough data for a network to learn with high accuracy. The idea is to take a model trained on a large dataset and transfer its knowledge to a smaller dataset. All convolutional layers are frozen, and training is done on the last few fully connected layers. Another approach is to make a custom CNN for COVID-19 CT scans. Based on this criterion, all

TABLE I.
SUMMARY OF DEEP LEARNING METHODS FOR COVID-19 DETECTION FROM LUNG CT SCANS

Papers	C/NC	Networks architecture	Datasets	Performance
[16]	NC	AlexNet, VGG-16, VGG-19, SqueezeNet, GoogleNet, MobileNet-V2, ResNet-18, ResNet-50, ResNet-101, and Xception	1020 CT (108 patients and 86 patients with other atypical and viral pneumonia diseases)	ResNet101 – ACC[a]=99.51%, AUC[b]=99.4%, TPR[c]=100%, TNR[d]=99.02% Xception - ACC=99.02%, AUC=99.4%, TPR=98.04%, TNR=100%
[17]	C	eXplainable Deep Learning approach (xDNN)	COVID: 1252 CT non-COVID: 1230 CT Brazil	F1[e]=97.31%
[18]	C	3 alternating convolution and pooling layers	COVID: 168 CT non-COVID: 168 CT	ACC= 96.28%, AUC = 98.08%, TPR=97.92%
[19]	C and NC	simple CNN and modified pre-trained AlexNet model	COVID: 203 CT non-COVID: 153 CT	pre-trained network - ACC=98% modified CNN - ACC=94.1%
[20]	C and NC	CTnet-10, DenseNet-169, VGG-16, ResNet-50, InceptionV3, and VGG-19	COVID: 349 CT non-COVID: 389 CT China	CTnet-10 - ACC=82.1% VGG19 - ACC=94,52%
[21]	C	multi-scale convolutional neural network (MSCNN)	COVID: 416 CT (206 patients) CAP: 412 CT (412 patients)	TPR=99.5% TNR=95.6%
[22]	NC	VGG16, VGG19, InceptionV3, InceptionResNetV2, Xception, DenseNet121, DenseNet169, and DenseNet201	COVID: 349 CT non-COVID: 397 CT China	DenseNet201 - ACC=85%, TPR=81%, TNR=89%
[23]	NC	VGG16/VGG19, Resnet50, InceptionV3, Xception, InceptionResNet, DenseNet, and NASNetLarge	COVID: 349 CT non-COVID: 363 CT China	VGG19 - COVID: TPR=83%, F1=81% non-COVID: TPR=81%, F1=83%
[24]	C	ResNet-50 was pretrained using ImageNet dataset and was used as backbone of UNet++	46096 CT (51 COVID-19 patients and 55 control patients of other diseases) China	external data: ACC=96% internal data: ACC=95.24% per-patient, ACC=98.85% per-image
[25]	C	Machine-driven design: COVID-Net CT-2	194922 CT (multinational cohort of 3745 patients)	COVID: TPR=98.2%, TNR=98.8% CAP[f]: TPR=96.2%, TNR=99% non-COVID: TPR=99%, TNR=99.5% ACC=98.1%
[26]	C	COVID-19 detection neural network (COVNet)	COVID-19: 1296 CT non-COVID: 1325 CT CAP: 1735 CT	COVID: TPR=90%, TNR=96%, AUC=96% CAP: TPR=87%, TNR=92%, AUC=95%
[27]	NC	FCN-8s, U-Net, V-Net, 3D U-Net++ 12, DPN-92 16 , Inception-v3, ResNet-50, and Attention ResNet-50	COVID: 723 CT non-COVID: 413 CT, China	ResNet-50 - TPR=97.4%, TNR=92.2%, AUC=99.1%
[28]	C	Pretrained ResNet152 as a backbone of 2D classification neural network	11356 CT (COVID-19, CAP, influenza and non-COVID) China and Russia	COVID: TPR=87.03%, TNR=96.6% CAP: AUC=98.04% influenza: AUC=98.85% non-COVID: AUC=97.52%
[29]	NC	ResNet50 2D CNN pretrained on ImageNet	COVID: 829 CT non-COVID: 1036 CT China and USA	ACC=94%, AUC=99.6%, TPR=98.2%, TNR= 92.2%
[30]	C	The location-attention classification model was built on the backbone of ResNet-18 by concatenating the location-attention mechanism in the full-connection layer	COVID: 219 CT (110 patients) influenza: 224 CT (224 patients) non-COVID: 175 CT China	ACC=86.7%
[31]	NC	VGG16, ResNet-50, Inception-v3, and Xception	COVID: 1194 CT other pneumonia: 1357 CT non-COVID: 998 CT	ResNet-50: ACC=99.87%, TPR=99.58%, TNR=100.00%

[a] ACC – Accuracy, [b] AUC – Area Under the ROC Curve, [c] TPR – True Positive Rate or Sensitivity, [d] TNR – True Negative Rate or Specificity, [e] F1 – F1 score, [f] CAP - Community-Acquired Pneumonia

networks in Table I are marked as C (custom-made) or NC (non-custom-made).

A number of papers focus on trying out various popular CNN models in order to find the best one. In [16] authors have used ten well-known CNNs to classify CT scans based on the presence of the COVID-19. The best performance was achieved by ResNet-101 and Xception with the same AUC of 99.4% which is significantly higher than the performance of the radiologist (AUC of 87.3%). In addition to the development of their own model for CT scan classification called CTnet-10, which has the accuracy of 82.1%, Shah et al. [20] have tested standard CNN models. The VGG-19 proved to be superior with an accuracy of 94.52%. Similar work has been done by Do and Vu in [22]. In their case, DenseNet201 is the highest performing model. The system developed in [27] is deployed in 16 hospitals in China. From all the models that authors have tried, ResNet-50 achieved the best results with AUC of 99.1%. Ko et al. have used four state-of-the-art pretrained deep learning models as a backbone of their classification network called FCONet [31]. ResNet-50 showed excellent diagnostic performance (sensitivity 99.58%, specificity 100.00%, and accuracy 99.87%) and outperformed the other three pretrained models on the testing data set.

Even though the main purpose of the work done in [17] is the presentation of the new dataset, the authors have given a baseline model (eXplainable Deep Learning-xDNN) that can achieve F1 score of promising 97.31%.

Several papers integrated multiple data types (CT scans, X-Rays, and Ultrasound images) in hope that more data will improve model performance. Authors in [18] have engineered the CNN-tailored deep neural network which achieves an overall accuracy of 96.28% when tested on both chest X-ray and CT scan images. On the same type of images, Maghdid et al. [19] have applied two models: simple CNN and modified pretrained AlexNet model. Pretrained model gives better accuracy of 98%. Horry et al. [23] fused all three types of medical images. They have first selected VGG19 from several popular CNN models as the most promising one. With extensive image preprocessing and parameter tuning, the model accomplished precision of up to 86% for X-Ray, 100% for Ultrasound, and 84% for CT scans.

A multi-scale convolutional neural network (MSCNN) was used in the artificial intelligence system in [21]. Under the limited number of training data, system diagnostic performance in differentiating COVID-19 from other common pneumonia is promising.

Li et al. [26] have developed COVID-19 detection neural network (COVNet) to extract the features from CT scans. Based on those features networks detects coronavirus infection in patients. COVNet was trained on over 4357 chest CT images from 3322 patients which are not shared publicly. AUC for COVID-19 and CAP scans is 96% and 95%, respectively. ResNet50 based CNN with transfer learning from ImageNet weights is presented in [29]. The model has 94% accuracy.

Authors in [30] have used models with location-attention mechanisms to classify CT scans of COVID-19, influenza-A, and healthy patients. Firstly, candidate infection regions are segmented out of the pulmonary CT images using a 3D deep learning model. These new images are then categorized using the location-attention classification model. Finally, infection type and overall confidence score were calculated using the Noisy-or Bayes function. This method has an accuracy rate of 86.7%.

Most of the previously described approaches use small datasets of the order of several hundred to several thousand CT scans. Since deep neural networks require a large amount of data, it is expected that authors that have worked with tens or hundreds of thousands of CT scans have developed state-of-the-art models. For example, Jin et al. [28] have developed and evaluated AI system for rapid COVID-19 detection on the dataset with more than 10 thousand CT scans of COVID-19, influenza-A/B, Community-Acquired Pneumonia (CAP), and non-pneumonia subjects. They have tested their system on other publicly available data and got AUC of more than 92%. Another excellent work is COVID Net CT-2 deep neural network presented in [25]. The authors have also introduced COVIDx-CT, a benchmark CT image dataset from multinational patients as a part of their COVID-Net open source initiative. On this dataset, COVID Net CT-2 obtains an accuracy of 98.1%. Chen et al. [24] have also engineered a high-performing model with per-patient accuracy of 95.24% and per-image accuracy of 98.85%. The model was trained on 46096 anonymous images of 106 admitted patients. Images are not publicly available.

III. Dataset Analysis

Data is essential for machine learning techniques. In order to support further AI research related to COVID-19, Table II represents a list of publicly available datasets of CT scans obtained from hospitals all over the world.

TABLE II.
AVAILABLE DATA SOURCES WITH COVID-19 LUNG CT SCANS

Source	Description
University of California San Diego [32]	349 COVID CT scans from 216 patients and 496 non-COVID CTs
MedSeg [33]	9 volumes, total of >800 slices, includes >350 COVID-19 annotated slices
Italian Society of Medical and Interventional Radiology [34]	100 axial CT scans from >40 patients with COVID
CC-CCII [35]	617,755 CT slices from 4154 patients (NCP, CP and healthy)
MosMedData [36]	1110 CT scans from 1100 patients from Russia
Kaggle [17]	1252 COVID CT scans and 1230 non-COVID CT scans From Brazil
BIMCV [37]	6687 CT scans from Spain
COVID-CT-MD [38]	171 COVID CT scans
University of Montreal [39]	203 COVID CT scans and 153 non-COVID CT scans
University of Macau [40]	416 CT scans from 206 patients with positive PCR and 412 non-COVID-19 pneumonia scans
COVID-Net Open Source Initiative [25]	201,103 CT slices from 4501 patients – multinational cohort

Certain datasets come primarily from medical research papers and contain lung images from COVID-19 patients exclusively [34, 37]. In [33] authors have collected 9 whole volumes with more than 800 slices. The radiologist evaluated 373 slices as positive and segmented them (COVID-19 masks).

Valencian Region Medical Image Bank in its first iteration obtained data (chest X-Rays, along with CT scans) from 11 hospitals [37]. All consecutive studies of patients with at least one positive RT-PCR test or positive immunological tests (IgM, IgG, or IgA) for SARS-Cov-2 were identified from the Health Information Systems in the Valencian Region and included in the BIMCV COVID-19+ dataset.

Many datasets include CT scans not only of patients infected by COVID-19, but other types of pneumonia (bacterial or viral), and healthy patients. The COVID-CT-MD dataset [38] contains volumetric chest CT scans of 171 patients (108 male, 63 female, 51.6+14.6 years) positive for COVID-19 infection, 60 patients (35 male, 25 female, 57.7+21.7 years) with CAP, and 76 healthy patients (40 male, 36 female, 43.4+14.1 years). All these cases are collected from Babak Imaging Center in Tehran, Iran, and labeled by three experienced radiologists in patient-level, slice-level, and lobe-level manners. Diagnosis of COVID-19 infection is based on RT-PCR test results, clinical parameters, or CT scan manifestations identified by thoracic radiologists.

Cohen et al. made a public open dataset [39] of chest X-ray and CT images of patients who are positive or suspected of COVID-19, or other viral and bacterial pneumonia (MERS, SARS, and ARDS.). Data is collected from public sources as well as through indirect collection from hospitals and physicians.

The dataset in [40] contains 416 COVID-19 positive CT scans and 412 common pneumonia (CP) CT scans from two hospitals in China. COVID-19 patients were confirmed positive by RT-PCR. CP patients were randomly selected and consisted of non-COVID-19 laboratory-confirmed bacterial pneumonia, mycoplasma pneumonia, fungal pneumonia, and viral pneumonia.

Authors in [32] built an open-sourced dataset from 760 medRxiv and bioRxiv preprints about COVID-19. Reported CT images were extracted and those containing clinical findings of COVID-19 were manually selected by reading the captions of the images. For each CT image, the meta-information was extracted from the paper, such as patient age, gender, location, medical history, scan time, the severity of COVID-19, and radiology report. The final dataset contains 349 COVID-19 CT images from 216 patients and 463 non-COVID-19 CT images.

Morozov et al. [36] created the dataset containing 1110 anonymized human lung CT scans from 1100 patients (42% males, 56% females, 2% other/unknown; aged 18 to 97 years old, median age 47) with COVID-19 related findings, as well as without such findings from medical hospitals in Moscow, Russia.

Data collected in [17] was acquired from hospital patients from Sao Paulo, Brazil. The dataset consists of 2482 CT scans in total, 1252 CT scans positive for COVID-19, and 1230 CT negative scans.

The biggest and the most complete among all datasets are presented in [35] and [25]. The first one consists of more than 600 thousand CT slice images from the China Consortium of Chest CT Image Investigation (CC-CCII) [35]. 750 CTs were manually segmented into the background, lung field, ground-grass opacity, and consolidation. COVID-19 cases were confirmed with RT-PCR, and all other types of pneumonia (viral pneumonia including adenoviral, influenza, and parainfluenza pneumonia, bacterial pneumonia, and mycoplasma pneumonia) were diagnosed on standard clinical, radiological, culture/molecular assay results. The second dataset is divided into two variants: "A" that consists of cases with confirmed diagnoses (RRT-PCR, radiologist-confirmed, etc.) and "B" which contains all of the "A" variant and adds some cases which are assumed to be correctly diagnosed but are weakly verified. COVIDx CT-2A and CT-2B datasets comprise of 194,922 CT slices from 3,745 patients and 201,103 CT slices from 4501 patients, respectively. This dataset is released as a directory of images and associated label files indicating classes (Normal, Pneumonia, and COVID-19) and bounding boxes for the body region [25].

IV. Discussion

The problem of CT classification is not purely a binary problem. Some papers consider a problem of multi-class classification where deep CNNs are able to distinguish different types of pneumonia originating from COVID, influenza, and CAP CTs.

Out of all papers that cover non-custom-made deep CNN, ResNets appear to have the best results. Authors claim extremely satisfactory performance metrics over 95% on the own test data which can be observed in Table I.

The network architecture that stood out, as the custom-made representative, is COVID-Net CT-2 [25]. It has low architectural and computational complexity and outstanding accuracy on their grand dataset. Authors leveraged the COVID-Net CT network architecture [41] as the core of the COVID-Net CT-2 network which was discovered automatically via machine-driven design exploration. Notable characteristics include high architectural diversity, selective long-range connectivity, and lightweight design patterns - heavy use of unstrided and strided projection-replication-projection-expansion as shown in Fig. 1. COVID-Net CT-2’s high sensitivity ensures few false negatives, which would lead to missed patients with COVID-19 infections, whereas high PPV ensures few false positives. Overall network accuracy is over 98%, which is remarkable. This paper has another significant contribution. The authors have presented a large and diverse publicly available dataset with over 200,000 CT scans and detailed metadata. This dataset comprises data from at least 15 different hospitals from all over the world.

One of the major challenges when it comes to the practical implementation of COVID-19 detection systems

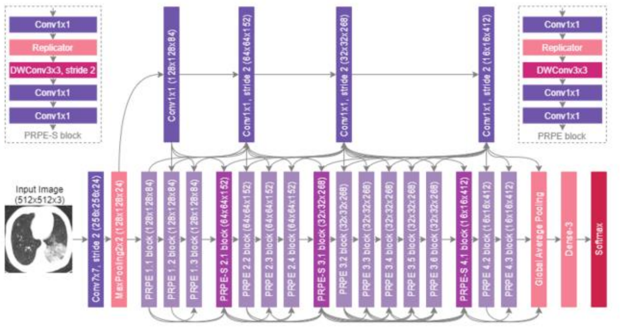

Figure 1. Architectural diagram of COVID-Net CT-2 [25]

in hospitals is a lack of adequate explanation of CNN model decisions. Classification models do not provide additional information to radiologists or medical specialists like segmented images or areas of interest. Diagnosis results of the AI system should be quantitatively explained in the original image to alleviate the drawback of deep CNN as a black box.

Efforts in creating bigger and richer datasets are undoubtedly noticeable. However, there is a strong need for higher quality control during the collection, storage, and processing of the data. Currently available datasets, summarized in Table II, are stored in various formats and standards that hinder the further development of COVID-19 related AI research. Some datasets are not diverse enough considering patients from only one region or country. Also, the gender, age, or other potentially useful information about the patient like the stage of the illness are not known. For an AI algorithm to work properly ratio of the CT scans coming from healthy and infected subjects should be balanced.

Huge efforts are needed for an AI system to be effective and useful: appropriate data processing, model selection, remodeling and retraining, continuous performance monitoring, and validation to facilitate continuous deployment. There are AI ethics principles for each phase of the AI system lifecycle especially when most AI applications against COVID-19 involve humans. The more AI applications are proposed, the more these applications need to ensure safety, privacy protection, and data security.

V. Conclusion and Future Work

In this paper, an extensive survey of Deep Convolutional Neural Networks for COVID-19 detection from Computed Tomography (CT) scans is presented. We provide detailed summaries of currently representative work, including available resources. We hope that this survey with broad bibliography gives significant insight into this domain and encourages new research and development. Such efforts will have a far-reaching impact with positive results to the post-COVID-19 pandemic period.

Data fusion concept allows combining multiple modes of data to improve model classification performance. Therefore, there is a certain potential in creating deep CNN able to process all CT scans, X-Ray, and Ultrasound images [23].

Many studies use various deep learning methods applied on different datasets and their performance is evaluated based on different criteria. Therefore, there is a demand for future work on developing a standardized benchmark framework to uniformly validate and compare the existing methods on the unique and diverse dataset.

References

[1] "WHO Coronavirus Disease (COVID-19) Dashboard," World Health Organization, 17 Feb 2021. [Online]. Available: https://covid19.who.int/. [Accessed 17 Feb 2021].

[2] E. Petersen, M. Koopmans, U. Go, D. H. Hamer, N. Petrosillo, F. Castelli, M. Storgaard, S. Al Khalili and L. Simonsen, "Comparing SARS-CoV-2 with SARS-CoV and influenza pandemics," *The Lancet infectious diseases,* 2020.

[3] T. Davenport and R. Kalakota, "The potential for artificial intelligence in healthcare," *Future healthcare journal,* vol. 6, no. 2, p. 94, 2019.

[4] T. Ai, Z. Yang, H. Hou, C. Zhan, C. Chen, W. Lv, Q. Tao, Z. Sun and L. Xia, "Correlation of chest CT and RT-PCR testing for coronavirus disease 2019 (COVID-19) in China: a report of 1014 cases," *Radiology,* vol. 296, no. 2, pp. E32-E40, 2020.

[5] R. Yamashita, M. Nishio, R. K. G. Do and K. Togashi, "Convolutional neural networks: an overview and application in radiology," *Insights into imaging,* vol. 9, no. 4, pp. 611-629, 2018.

[6] M. A. Mazurowski, M. Buda, A. Saha and M. R. Bashir, "Deep learning in radiology: An overview of the concepts and a survey of the state of the art with focus on MRI," *Journal of magnetic resonance imaging,* vol. 49, no. 4, pp. 939-954, 2019.

[7] A. Krizhevsky, I. Sutskever and G. E. Hinton, "Imagenet classification with deep convolutional neural networks," *Advances in neural information processing systems,* vol. 25, pp. 1097-1105, 2012.

[8] K. He, X. Zhang, S. Ren and J. Sun, "Deep residual learning for image recognition," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2016.

[9] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," *arXiv preprint arXiv:1409.1556,* 2014.

[10] C. Francois, "Xception: Deep learning with depthwise separable convolutions," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2017.

[11] G. Huang, L. Zhuang, L. Van Der Maaten and K. Q. Weinberger, "Densely connected convolutional networks," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2017.

[12] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens and Z. Wojna, "Proceedings of the IEEE conference on computer vision and pattern recognition," 2016, pp. 2818-2826.

[13] T. T. Nguyen, "Artificial intelligence in the battle against coronavirus (COVID-19): a survey and future research directions," *arXiv preprint arXiv:2008.07343,* 2020.

[14] S. Lalmuanawma, J. Hussain and L. Chhakchhuak, "Applications of machine learning and artificial intelligence for Covid-19 (SARS-CoV-2) pandemic: A review," *Chaos, Solitons & Fractals,* p. 110059, 2020.

[15] A. Ulhaq, J. Born, A. Khan, D. P. S. Gomes, S. Chakraborty and M. Paul, "Covid-19 control by computer vision approaches: A survey," *IEEE Access,* vol. 8, pp. 179437-179456, 2020.

[16] A. A. Ardakani, A. R. Kanafi, U. R. Acharya, N. Khadem and A. Mohammadi, "Application of deep learning technique to manage COVID-19 in routine clinical practice using CT images: Results of 10 convolutional neural networks," *Computers in Biology and Medicine,* p. 103795, 2020.

[17] P. Angelov and E. Almeida Soares, "SARS-CoV-2 CT-scan dataset: A large dataset of real patients CT scans for SARS-CoV-2 identification," *medRxiv,* 2020.

[18] H. Mukherjee, S. Ghosh, A. Dhar, S. M. Obaidullah, K. Santosh and K. Roy, "Deep neural network to detect COVID-19: one architecture for both CT Scans and Chest X-rays," *Applied Intelligence*, pp. 1-13, 2020.

[19] H. S. Maghdid, A. T. Asaad, K. Z. Ghafoor, A. S. Sadiq and M. K. Khan, "Diagnosing COVID-19 pneumonia from X-ray and CT images using deep learning and transfer learning algorithms," *arXiv preprint arXiv:2004.00038,* 2020.

[20] V. Shah, R. Keniya, A. Shridharani, M. Punjabi, J. Shah and N. Mehendale, "Diagnosis of COVID-19 using CT scan images and deep learning techniques," *Emergency radiology,* pp. 1-9, 2021.

[21] T. Yan, P. K. Wong, H. Ren, H. Wang, J. Wang and Y. Li, "Automatic distinction between covid-19 and common pneumonia using multi-scale convolutional neural network on chest ct scans," *Chaos, Solitons & Fractals,* vol. 140, p. 110153, 2020.

[22] C. Do and L. Vu, "An approach for recognizing COVID-19 cases using Convolutional Neural Networks applied to CT scan images," in *Applications of Digital Image Processing XLIII*, vol. 11510, International Society for Optics and Photonics, 2020, p. 1151034.

[23] M. J. Horry, S. Chakraborty, M. Paul, A. Ulhaq, B. Pradhan, M. Saha and N. Shukla, "COVID-19 detection through transfer learning using multimodal imaging data," *IEEE Access,* vol. 8, pp. 149808-149824, 2020.

[24] J. Chen, L. Wu, J. Zhang, L. Zhang, D. Gong, Y. Zhao, Q. Chen, S. Huang, M. Yang, X. Yang and others, "Deep learning-based model for detecting 2019 novel coronavirus pneumonia on high-resolution computed tomography," *Scientific reports,* vol. 10, pp. 1-11, 2020.

[25] H. Gunraj, A. Sabri, D. Koff and A. Wong, "COVID-Net CT-2: Enhanced Deep Neural Networks for Detection of COVID-19 from Chest CT Images Through Bigger, More Diverse Learning," *arXiv preprint arXiv:2101.07433,* 2021.

[26] L. Li, L. Qin, Z. Xu, Y. Yin, X. Wang, B. Kong, J. Bai, Y. Lu, Z. Fang, Q. Song and others, "Artificial intelligence distinguishes COVID-19 from community acquired pneumonia on chest CT," *Radiology,* 2020.

[27] S. Jin, B. Wang, H. Xu, C. Luo, L. Wei, W. Zhao, X. Hou, W. Ma, Z. Xu, Z. Zheng and others, "AI-assisted CT imaging analysis for COVID-19 screening: Building and deploying a medical AI system in four weeks," *MedRxiv,* 2020.

[28] C. Jin, W. Chen, Y. Cao, Z. Xu, Z. Tan, X. Zhang, L. Deng, C. Zheng, J. Zhou and H. a. o. Shi, "Development and evaluation of an artificial intelligence system for COVID-19 diagnosis," *Nature communications,* vol. 11, no. 1, pp. 1-14, 2020.

[29] O. Gozes, M. Frid-Adar, H. Greenspan, P. D. Browning, H. Zhang, W. Ji, A. Bernheim and 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," *arXiv preprint arXiv:2003.05037,* 2020.

[30] X. Xu, X. Jiang, C. Ma, P. Du, X. Li, S. Lv, L. Yu, Q. Ni, Y. Chen, J. Su and others, "A deep learning system to screen novel coronavirus disease 2019 pneumonia," *Engineering,* vol. 6, pp. 1122-1129, 2020.

[31] H. Ko, H. Chung, W. S. Kang, K. W. Kim, Y. Shin, S. J. Kang, J. H. Lee, Y. J. Kim, N. Y. Kim, H. Jung and others, "COVID-19 pneumonia diagnosis using a simple 2D deep learning framework with a single chest CT image: model development and validation," *Journal of medical Internet research,* vol. 22, no. 6, p. e19569, 2020.

[32] X. Yang, X. He, J. Zhao, Y. Zhang and P. Xie, "COVID-CT-Dataset: A CT Image Dataset about COVID-19," *arXiv preprint arXiv:2003.13865*, 2020.

[33] "COVID-19 CT segmentation dataset," [Online]. Available: http://medicalsegmentation.com/covid19/.

[34] "COVID-19 DATABASE," [Online]. Available: https://www.sirm.org/category/senza-categoria/covid-19/.

[35] K. Zhang, X. Liu, J. Shen, Z. Li, Y. Sang, X. Wu, Y. Zha, W. Liang, C. Wang, K. Wang and others, "Clinically applicable AI system for accurate diagnosis, quantitative measurements, and prognosis of COVID-19 pneumonia using computed tomography," *Cell,* vol. 181, no. 6, pp. 1423-1433, 2020.

[36] S. P. Morozov, A. E. Andreychenko, I. A. Blokhin, P. B. Gelezhe, A. P. Gonchar, A. E. Nikolaev, N. A. Pavlov, V. Y. Chernina and V. A. Gombolevskiy, "MosMedData: data set of 1110 chest CT scans performed during the COVID-19 epidemic," *Digital Diagnostics,* vol. 1, no. 1, pp. 49-59, 2020.

[37] M. De La Iglesia Vayá, J. M. Saborit, J. A. Montell, A. Pertusa, A. Bustos, M. Cazorla, J. Galant, X. Barber, D. Orozco-Beltrán, F. García-García and others, "Bimcv covid-19+: a large annotated dataset of rx and ct images from covid-19 patients," *arXiv preprint arXiv:2006.01174,* 2020.

[38] P. Afshar, S. Heidarian, N. Enshaei, F. Naderkhani, M. J. Rafiee, A. Oikonomou, F. B. Fard, K. Samimi, K. N. Plataniotis and A. Mohammadi, "COVID-CT-MD: COVID-19 Computed Tomography (CT) Scan Dataset Applicable in Machine Learning and Deep Learning," *arXiv preprint arXiv:2009.14623,* 2020.

[39] J. P. Cohen, P. Morrison, L. Dao, K. Roth, T. Q. Duong and M. Ghassemi, "Covid-19 image data collection: Prospective predictions are the future," *arXiv preprint arXiv:2006.11988,* 2020.

[40] J. Yan, *COVID-19 and common pneumonia chest CT dataset,* Mendeley, 2020.

[41] H. Gunraj, L. Wang and A. Wong, "Covidnet-ct: A tailored deep convolutional neural network design for detection of covid-19 cases from chest ct images," *Frontiers in medicine,* vol. 7, 2020.

[42] S. G. Armato III, G. McLennan, L. Bidaut, M. F. McNitt-Gray, C. R. Meyer, A. P. Reeves, B. Zhao, D. R. Aberle, C. I. Henschke, E. A. Hoffman and others, "The lung image database consortium (LIDC) and image database resource initiative (IDRI): a completed reference database of lung nodules on CT scans," *Medical physics,* vol. 38, no. 2, pp. 915-931, 2011.