A Lightweight Deep Learning Model for COVID-19 Detection

1st Siti Raihanah Abdani
Department of Electrical, Electronic and Systems Engineering
Universiti Kebangsaan Malaysia
Bangi, Malaysia

2nd Mohd Asyraf Zulkifley
Department of Electrical, Electronic and Systems Engineering
Universiti Kebangsaan Malaysia
Bangi, Malaysia
asyraf.zulkifley@ukm.edu.my

3rd Nuraisyah Hani Zulkifley
Community Health Department
Universiti Putra Malaysia
Serdang, Malaysia

***Abstract*—COVID-19 is a contagious disease that has caused more than 230,000 deaths worldwide at the end of April 2020. Within a span of just a few months, it has infected more than 4 million peoples across the globe due to its high transmittance rate. Thus, many governments have tried their best to increase the diagnostic capability of their hospitals so that the disease can be identified as early as possible. However, in most cases, the results only come back after a day or two, which directly increases the possibility of disease spreadness because of the delayed diagnosis. Therefore, a fast screening method using existing tools such as x-ray and computerized tomography scans can help alleviate the burden of mass diagnosis tests. A chest x-ray is one of the best modalities in diagnosing a pneumonia symptom, which is the primary symptom for COVID-19. Hence, this paper proposes a lightweight deep learning model to screen the possibility of COVID-19 accurately. A lightweight model is important, as such it allows the model to be deployed on various platforms that include mobile phones, tablets, and normal computers without worrying about the memory storage capacity. The proposed model is based on 14 layers of convolutional neural network with a modified spatial pyramid pooling module. The multi-scale ability of the proposed network allows it to identify the COVID-19 disease for various severity levels. According to the performance results, the proposed SPP-COVID-Net achieves the best mean accuracy of 0.946 with the lowest standard deviation among the training folds accuracy. It comprises of just 862,331 total number of parameters, which uses less than 4 MegaBytes memory storage. The model is suitable to be implemented for fast screening purposes so that better-targeted diagnoses can be performed to optimize the test time and cost.**

***Index Terms*—COVID-19 Detection, Lightweight Deep Learning Network, Compact Deep Learning**

I. Introduction

COVID-19, which was first reported in Wuhan, China is a dangerous disease that affects mostly human respiratory function [1]. Even though the mortality rate is not high, which is less than 5%, but it can be transmitted easily between humans, even with minimal contact. Thus, it is hard to contain its spreadness and instigates many governments to order lock-down procedures throughout the world [2]. It is done with the intention of minimizing the physical contacts and thus curbs the disease transmission. The social distancing term has been popularized inline with the philosophy of reducing human contact, which mandates each person to observe his proximity distance to the other peoples. This step is extremely crucial for confined space services such as lift where the users must stand at least a meter from the others, which directly reducing the limit it can carry on at one time.

COVID-19SARS-CoV-2 is the original virus strain that causes the COVID-19 disease, which has evolved into several different mutated strains [3]. The main disorder that is commonly associated with this disease is the difficulty in breathing which can lead to acute pneumonia [4]. One of the cheapest ways to screen the possibility of pneumonia is through a chest x-ray. By having an image of a chest x-ray, the medical practitioners can observe the possibility of respiratory problems [5]. It is also a cheaper and faster way compared to the standard diagnosis procedures that can take up to three days to get a confirmation result. Due to the contagious nature of the COVID-19, a fast screening method is needed so that the positively screened patient can be quarantined as soon as possible [6]. It is not optimal to diagnose all possible candidates as the cost is astronomical for the government, especially for the developing countries.

Fig. 1. Some samples of x-ray images.

According to Atif et al. [7], the cost of processing an x-ray image is less than RM 10, while a standard COVID-19 swab test can cost more than RM 350 per swab [8]. Apart from the cost, the swab test also requires dedicated test facilities to process the samples and there will be a limit number of test can be processed daily. Hence, an x-ray based approach is a good screening choice for the government as it can be captured efficiently given the widespread availability of x-ray machines. Some samples of x-ray images are shown in Figure 1. It also a cheaper option and many doctors are trained to find the possibility of pneumonia based on chest x-ray images. In

© IEEE 2020. This article is free to access and download, along with rights for full text and data mining, re-use and analysis.

Authorized licensed use limited to: IEEE Xplore. Downloaded on September 17,2020 at 14:54:29 UTC from IEEE Xplore. Restrictions apply.

order to automate the screening process, where the doctors are already burdened with many tasks in this pandemic situation, a lightweight deep learning model is proposed to screen the possibility of COVID-19 disease accurately and efficiently.

In this paper, several lightweight deep learning models will be analyzed to find the optimal model, specifically for mobile applications. A lightweight deep learning model is defined to be a network with a total number of parameters less than 5,000,000. Its main advantage is the low size of memory requirement, which makes it suitable to be implemented for mobile applications. Usually, a lightweight deep learning model is built upon a compact architecture [9], [10]. A medical practitioner can directly download the model and run it immediately in order to automate the screening process. It will only use a small portion of phone memory storage and indirectly makes the screening process faster [11]. In fact, the radiographers can take a lot of x-ray images independently, before passing the captured images to the automatic screening system, which will reduce the burden of medical practitioners.

Given the importance of having a good screening model, an accurate lightweight deep learning network is proposed by embedding a modified spatial pyramid pooling (SPP) module [12] to the convolutional neural network (CNN). By integrating the modified SPP module, several input scales can be processed in parallel [13]. The proposed model is called SPP-COVID-Net and has a total of just 862,331 parameters. The basis of this network is derived from DarkCovid-Net [14], in which a multi-scale approach is embedded by replacing the last few layers of the original network with the parallel pooling layers of SPP. The system must be made robust to various input scales so that it can cater to variability in the capturing process of x-ray images. A robust detection system is needed so that the system accuracy still retain the same level of detection given various challenge posed by the input data as argued in [15].

This paper is organized into five main sections. Section II discusses some recent related works, focuses on COVID-19 screening and diagnosis algorithms. Section III explains the proposed SPP-COVID-Net by integrating the SPP module into DarkCovid-Net. Classifications results of several lightweight deep learning models are then compared with the proposed method in Section IV before a concise conclusion is given in the last section.

II. Related Works

This section summarizes some works that are related to COVID-19 detection, particularly algorithms that are based on x-ray and computerized tomography (CT) scan. It should be noted that a CT scan approach is the gold standard for detecting a pneumonia condition, but a chest x-ray modality is the cheaper and faster way. In general, it is still difficult for an inexperienced radiologist to differentiate the white patches on the scan that was caused by the pneumonia condition. Therefore, an automatic tool can be a great help in identifying the possibility of the disease in the early stage as shown in other successful applications [16], [17]. A concise review by Dong et al. [18] shows the importance of medical image in managing and treating the COVID-19 disease. One of the crucial points that have been argued is that an automatic tool is an efficient supplement to the laboratory-based real-time polymerase chain reaction (RT-PCR) test.

Pereira et al. [19] have analyzed two types of machine learning architectures to detect COVID-19, which are flat and hierarchical structures. They have also investigated various feature extraction methods to extract COVID-19 patterns, which can also distinguish between pneumonia caused by COVID-19SARS-CoV-2 and other viruses. They have tested their proposed method on a combined database, taken from three different resources, which have been augmented beforehand to deal with the imbalanced data issues. In [20], Abdel-Basset et al. focused on the x-ray segmentation method to extract the similar small regions that may represent COVID-19 features. They have introduced a hybrid COVID-19 detection model by applying an improved marine predators algorithm (IMPA). A method based on the DarkNet model using chest x-ray images was introduced by Ozturk et al. [14]. They experimented on two different setups, which are are binary classification (COVID-19 vs non-COVID-19) and three-class classification (COVID-19 vs normal vs other types of viral pneumonia). Their experimental results show that they achieved accuracies of 98.08% and 87.02% for binary and three-class classification, respectively.

Another COVID-19 detector was devised by Togacar et al. [21], where they have applied two deep learning model feature extractors, which are MobileNet V2 and SqueezeNet. The features are then classified by using the Support Vector Machine, which is not an end-to-end operation. Before that, the images underwent a pre-processing operation using the Fuzzy Colour technique. Their method managed to achieve a promising result of 99.72% accuracy. The results were obtained according to the three-class classification setup of COVID-19, normal, and pneumonia. In [22], the authors tackle the same problem of three-class classification problem as in [21]. A modified SqueezeNet model was devised using Bayesian optimization where the network error is used to optimize the hyper-parameters. Their method, COVIDiagnosis-Net utilized augmentation module to overcome the imbalanced distribution of data between the classes. The method has achieved 0.983 accuracy and they claimed that the network is optimized for mobile application.

III. SPP-COVID-Net

A. Chest X-ray Dataset

The same dataset used in [23] is utilized to verify the proposed SPP-COVID-Net performance. The dataset is constructed based on other online databases [24], [25], [26] that were taken from various countries. The full dataset consists of chest x-ray images of 219 patients of confirmed positive COVID-19, 1341 images of normal people and 1345 images of other types of viral pneumonia patient. Each of the x-ray images has a resolution of $1024x1024$ in the format

Authorized licensed use limited to: IEEE Xplore. Downloaded on September 17,2020 at 14:54:29 UTC from IEEE Xplore. Restrictions apply.

of Portable Network Graphics. Some samples of chest x-ray images of COVID-19, normal and other types of viral pneumonia patients are shown in Figure 2,3 and 4,respectively.

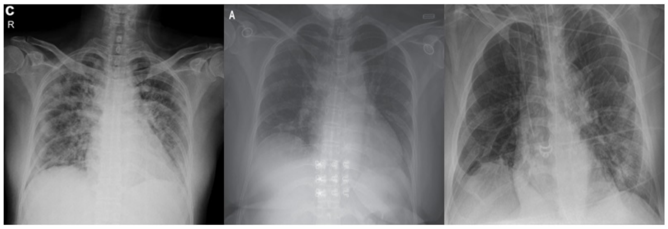

Fig. 2. Sample of chest x-ray images of COVID-19 patients.

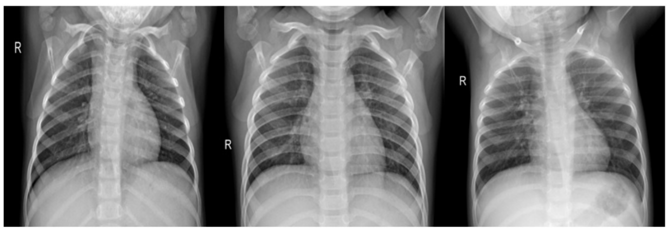

Fig. 3. Sample of chest x-ray images of normal patients.

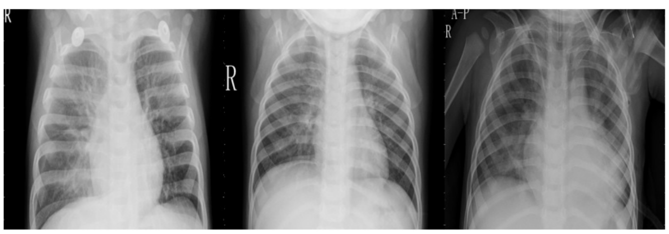

Fig. 4. Sample of chest x-ray images of other types of viral pneumonia patients.

B. Method

SPP-COVID-19 is a detection network that classifies an x-ray image into one of the three following classes, which are COVID-19, normal, and other types of viral pneumonia. The networks consist of 14 layers of normal CNN and one module of SPP. The full network architecture is shown in Table I, where our modified SPP module is shown in Figure 5. All 14 layers of normal CNN will be followed by batch normalization operation and Leaky ReLU activation function. Thus, all biases of the CNN layers will not be activated. The first two layers of CNN is setup without any squeeze operation, while the rest of the 12 CNN layers will adopt a squeeze scheme in the form of four-module, indicated by i. Each of the squeeze modules will consist of three CNN layers, where the initial number of filters, N_i will be twice the number of filter in the second CNN layer, $\frac{N_i}{2}$, while the third CNN layer will have the same number of filter as the first layer, N_i. The kernel size will be set to $3x3$ for the first and third layers, while it will be set to $1x1$ for the first layer. The total number of filters in each of the squeeze modules are set to $N = \{32, 64, 128, 256\}$.

TABLE I
ARCHITECTURE OF THE SPP-COVID-NET.

Layer No.	Operation	No. of Filter	Kernel	Stride
1	Conv2D	8	3x3	1x1
2	Conv2D	16	3x3	1x1
3	MaxPooling2D	-	2x2	2x2
4	Conv2D	32	3x3	1x1
5	Conv2D	16	1x1	1x1
6	Conv2D	32	3x3	1x1
7	MaxPooling2D	-	2x2	2x2
8	Conv2D	64	3x3	1x1
9	Conv2D	32	1x1	1x1
10	Conv2D	64	3x3	1x1
11	MaxPooling2D	-	2x2	2x2
12	Conv2D	128	3x3	1x1
13	Conv2D	64	1x1	1x1
14	Conv2D	128	3x3	1x1
15	MaxPooling2D	-	2x2	2x2
16	Conv2D	256	3x3	1x1
17	Conv2D	128	1x1	1x1
18	Conv2D	256	3x3	1x1
19	SPP module	-	4x4,6x6,7x7	1x1
20	Dense	3	-	-

For the modified SPP module, no convolutional operation is performed, instead, only the multiple scales of down pooling operation are utilized. In this paper, three maximum down pooling operations are executed in parallel with the kernel size of $4x4$,$6x6$, and $7x7$. Each of the pooling outputs will be flattened into a vector, where each vector will be concatenated into a single long vector. Then, a single layer of dense neural network is used to classify the images into their respective class using the SoftMax activation function.

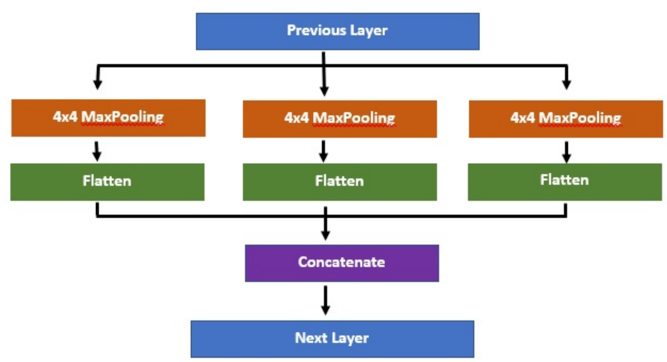

Fig. 5. Architecture of the modified SPP module.

C. Training and Validation

The raw code for SPP-COVID-Net can be downloaded from https://github.com/SitiRaihanah/SPP-COVID-Net/blob/master/SPP-COVID-Net.py1. It is coded on the Python platform using Keras front-end and TensorFlow back-end. Adam optimizer is used to train the network using categorical cross-entropy loss function with a total number of epoch equal to 100 and a learning rate of 0.0001. Minibatch

Authorized licensed use limited to: IEEE Xplore. Downloaded on September 17,2020 at 14:54:29 UTC from IEEE Xplore. Restrictions apply.

TABLE II
PERFORMANCE COMPARISON BETWEEN SPP-COVID-NET AND THE BENCH-MARKED METHODS IN CLASSIFYING CHEST X-RAY IMAGES OF COVID-19 PATIENTS.

Method	Total no. of Parameters	Fold-1	Fold-1	Fold-1	Fold-1	Fold-1	$\overline{\text{acc}}$	Variance	Standard Deviation
MobileNet V1	3,231,939	0.912	0.869	0.916	0.931	0.885	0.903	0.000626	0.0250
MobileNet V2	2,262,979	0.888	0.909	0.836	0.914	0.881	0.886	0.000944	0.0307
MobileNet V3 Small	1,665,501	0.897	0.912	0.735	0.919	0.899	0.872	0.00598	0.0774
MobileNet V3 Large	3,789,427	0.895	0.911	0.892	0.935	0.490	0.824	0.0353	0.188
ShuffleNet V1	939,531	0.474	0.926	0.845	0.904	0.851	0.800	0.0343	0.185
SquezeNet	**736,963**	0.952	0.948	0.957	0.959	0.497	0.862	0.0419	0.205
DarkCOVID-Net	1,167,363	0.957	0.940	0.947	0.947	0.909	0.940	0.000335	0.0183
SPP-COVID-Net	862,331	0.957	0.943	0.943	0.950	0.938	**0.946**	**0.0000531**	**0.00729**

size of 64 is used to train the network using a cross-validation scheme of five folds. The performance is measured using mean accuracy ($\overline{acc}$) metric as shown in the following equation, where n the is the total number of cross-validation folds, $\mathbf{C}$ is the set of available class, T_p is the true positive, T_n is the true negative, F_p is the false positive and F_n is the false negative detection.

$$acc_j = \frac{\sum_{i=0}^{|\mathbf{C}|} \frac{T_{p,i}+T_{n,i}}{T_{p,i}+T_{n,i}+F_{p,i}+F_{n,i}}}{c},\ ,\ i \in \mathbf{C} \tag{1}$$

$$\overline{acc} = \frac{\sum_{j=0}^{n} acc_j}{n} \tag{2}$$

IV. RESULTS AND DISCUSSION

For performance comparison, six more lightweight deep learning models are tested, which consist of MobileNet V1 [27], MobileNet V2 [28], MobileNet V3 [29], ShuffleNet V1 [30], SqueezeNet [31] and DarkCOVID-Net [14]. Each of the algorithms has gone through a 5-fold cross-validation test, where the full results are shown in Table II. In general, our SPP-COVID-Net produces the best mean accuracy of 0.946, followed by DarkCOVID-Net and MobileNet V1 with mean accuracy of 0.940 and 0.903, respectively. SPP-COVID-Net also achieves the best mean accuracy with fewer total parameters compared to the DarkCOVID-Net and MobileNet V1. In fact, among the benchmarked models, only three methods have a total number of parameters that are less than 1,000,000, which are SqueezeNet, SPP-COVID-Net, and ShuffleNet V1. It is important to have a model with low memory requirement but still deliver a good performance. In this case, only SPP-COVID-Net achieves a mean accuracy of more than 0.9 with less than 1,000,000 total parameters.

SPP-COVID-Net alters the few last layers of DarkCOVID-Net by embedding the modified SPP module. By processing multiple inputs with several max-pooling operators of different kernel sizes, the algorithm manages to detect the disease features in multi-scale form. For COVID-19 and other types of viral pneumonia patients, their x-ray images are expected to contain some abnormalities blobs compared to the normal patients. These blobs vary in size and hence, the algorithm should be able to detect them regardless of the disease severity. Normally, a larger blob size indicates that the disease is in the later stage and pose a more severe risk to the patients.

Besides that, Table II also shows the accuracy performance variation among the cross-validation folds. SPP-COVID-Net also returns the lowest standard deviation value of 0.00729, compared to the second-highest mean accuracy algorithm, DarkCOVID-Net with 0.0183 standard deviation. It shows that SPP-COVID-Net is more robust to variation in training data selection as the accuracy range is stable within $[0.938, 0.957]$.

V. CONCLUSION

In conclusion, the proposed SPP-COVID-Net has achieved a good mean accuracy compared to the bench-marked methods. In fact, it is the second most lightweight model with just 862,231 total number of parameters. In terms of training robustness, it is the most stable algorithm with a low accuracy variation among the cross-validation folds that produce accuracy readings within the range of $[0.938, 0.957]$. SPP-COVID-Net strength can be attributed to its ability to process multi-scale features because of the SPP module integration. The proposed algorithm is suitable for mobile phone applications, which can fasten the screening process of the COVID-19 disease.

ACKNOWLEDGMENT

The authors would like to acknowledge fundings from Universiti Kebangsaan Malaysia (Geran Universiti Penyelidikan: GUP-2019-008 and Ministry of Education Malaysia (Fundamental Research Grant Scheme: FRGS/1/2019/ICT02/UKM/02/1). The Titan V used for this research was donated by the NVIDIA Corporation.

REFERENCES

[1] D. Cao, H. Yin, J. Chen, F. Tang, M. Peng, R. Li, H. Xie, X. Wei, Y. Zhao, and G. Sun, "Clinical analysis of ten pregnant women with covid-19 in wuhan, china: A retrospective study," *International Journal of Infectious Diseases*, vol. 95, pp. 294 – 300, 2020. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S1201971220302630

[2] J. Bunyan, "Pm: Malaysia under movement control order from wed until march 31, all shops closed except for essential services," Online, Mar. 2020. [Online]. Available: https://www.malaymail.com/news/malaysia/2020/03/16/pm-malaysia-in-lockdown-from-wed-until- march-31-all-shops-closed/-except-for/1847204

[3] L. [van Dorp], M. Acman, D. Richard, L. P. Shaw, C. E. Ford, L. Ormond, C. J. Owen, J. Pang, C. C. Tan, F. A. Boshier, A. T. Ortiz, and F. Balloux, "Emergence of genomic diversity and recurrent mutations in sars-cov-2," *Infection, Genetics and Evolution*, p. 104351, 2020. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S1567134820301829

Authorized licensed use limited to: IEEE Xplore. Downloaded on September 17,2020 at 14:54:29 UTC from IEEE Xplore. Restrictions apply.

[4] S. Law, A. W. Leung, and C. Xu, "Severe acute respiratory syndrome (sars) and coronavirus disease-2019 (covid-19): From causes to preventions in hong kong," *International Journal of Infectious Diseases*, vol. 94, pp. 156 – 163, 2020. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S1201971220301922

[5] A. Jacobi, M. Chung, A. Bernheim, and C. Eber, "Portable chest x-ray in coronavirus disease-19 (covid-19): A pictorial review," *Clinical imaging*, vol. 64, p. 35—42, April 2020. [Online]. Available: https://europepmc.org/articles/PMC7141645

[6] A. M. Al-Awadhi, K. Alsaifi, A. Al-Awadhi, and S. Alhammadi, "Death and contagious infectious diseases: Impact of the covid-19 virus on stock market returns," *Journal of Behavioral and Experimental Finance*, vol. 27, p. 100326, 2020. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S2214635020300800

[7] M. Atif, S. A. Sulaiman, A. A. Shafie, F. Saleem, and N. Ahmad, "Determination of chest x-ray cost using activity based costing approach at penang general hospital, malaysia." *The Pan African medical journal*, vol. 12, no. 40, 2012.

[8] J. Chong, "Want us to test workers for covid-19?" May 2020. [Online]. Available: https://www.malaymail.com/news/malaysia/2020/05/06/want-us-to-test-workers-for-covid- 19-then-foot-the-bill-developers/-and-buil/1863746

[9] M. A. Zulkifley and N. Trigoni, "Multiple-model fully convolutional neural networks for single object tracking on thermal infrared video," *IEEE Access*, vol. 6, pp. 42 790–42 799, 2018.

[10] M. A. Zulkifley, "Two streams multiple-model object tracker for thermal infrared video," *IEEE Access*, vol. 7, pp. 32 383–32 392, 2019.

[11] S. R. Abdani, M. A. Zulkifley, and A. Hussain, "Compact convolutional neural networks for pterygium classification using transfer learning," in *IEEE International Conference on Signal and Image Processing Applications*, September 2019, pp. 140–143.

[12] K. He, X. Zhang, S. Ren, and J. Sun, "Spatial pyramid pooling in deep convolutional networks for visual recognition," in *Computer Vision – ECCV 2014*, D. Fleet, T. Pajdla, B. Schiele, and T. Tuytelaars, Eds. Cham: Springer International Publishing, 2014, pp. 346–361.

[13] S. R. Abdani and M. A. Zulkifley, "Densenet with spatial pyramid pooling for industrial oil palm plantation detection," in *2019 International Conference on Mechatronics, Robotics and Systems Engineering*, 2019.

[14] T. Ozturk, M. Talo, E. A. Yildirim, U. B. Baloglu, O. Yildirim, and U. R. Acharya], "Automated detection of covid-19 cases using deep neural networks with x-ray images," *Computers in Biology and Medicine*, vol. 121, p. 103792, 2020. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0010482520301621

[15] M. A. Zulkifley and B. Moran, "Enhancement of robust foreground detection through masked greyworld and color co-occurrence approach," in *3rd International Conference on Computer Science and Information Technology*, vol. 4, July 2010, pp. 131–136.

[16] M. A. Zulkifley, N. A. Mohamed, and N. H. Zulkifley, "Squat angle assessment through tracking body movements," *IEEE Access*, vol. 7, pp. 48 635–48 644, 2019.

[17] M. A. Zulkifley, S. R. Abdani, and N. H. Zulkifley, "Pterygium-net: A deep learning approach to pterygium detection and localization," *Multimedia Tools and Applications*, 2019.

[18] D. Dong, Z. Tang, S. Wang, H. Hui, L. Gong, Y. Lu, Z. Xue, H. Liao, F. Chen, F. Yang, R. Jin, K. Wang, Z. Liu, J. Wei, W. Mu, H. Zhang, J. Jiang, J. Tian, and H. Li, "The role of imaging in the detection and management of covid-19: a review," *IEEE Reviews in Biomedical Engineering*, pp. 1–1, 2020.

[19] R. M. Pereira, D. Bertolini, L. O. Teixeira, C. N. Silla, and Y. M. Costa, "Covid-19 identification in chest x-ray images on flat and hierarchical classification scenarios," *Computer Methods and Programs in Biomedicine*, p. 105532, 2020. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0169260720309664

[20] M. Abdel-Basset, R. Mohamed, M. Elhoseny, R. K. Chakrabortty, and M. Ryan, "A hybrid covid-19 detection model using an improved marine predators algorithm and a ranking-based diversity reduction strategy," *IEEE Access*, vol. 8, pp. 79 521–79 540, 2020.

[21] M. Togacar, B. Ergen, and Z. Cömert, "Covid-19 detection using deep learning models to exploit social mimic optimization and structured chest x-ray images using fuzzy color and stacking approaches," *Computers in Biology and Medicine*, vol. 121, p. 103805, 2020. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0010482520301736

[22] F. Ucar and D. Korkmaz, "Covidiagnosis-net: Deep bayes-squeezenet based diagnosis of the coronavirus disease 2019 (covid-19) from x-ray images," *Medical Hypotheses*, vol. 140, p. 109761, 2020. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0306987720307702

[23] M. E. H. Chowdhury, T. Rahman, A. Khandakar, R. Mazhar, M. A. Kadir, Z. B. Mahbub, K. R. Islam, M. S. Khan, A. Iqbal, N. Al-Emadi, and M. B. I. Reaz, "Can ai help in screening viral and covid-19 pneumonia?" 2020.

[24] "Covid-19: Casistica radiologica italiana," 2020. [Online]. Available: https://www.sirm.org/category/senza-categoria/covid-19/

[25] J. P. Cohen, P. Morrison, and L. Dao, "Covid-19 image data collection," *arXiv 2003.11597*, 2020. [Online]. Available: https://github.com/ieee8023/covid-chestxray-dataset

[26] P. Mooney, "Chest x-ray images (pneumonia)." [Online]. Available: https://www.kaggle.com/paultimothymooney/chest-xray-pneumonia

[27] A. G. Howard, M. Zhu, B. Chen, D. Kalenichenko, W. Wang, T. Weyand, M. Andreetto, and H. Adam, "Mobilenets: Efficient convolutional neural networks for mobile vision applications," *CoRR*, vol. abs/1704.04861, 2017. [Online]. Available: http://arxiv.org/abs/1704.04861

[28] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L. Chen, "Mobilenetv2: Inverted residuals and linear bottlenecks," in *2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2018, pp. 4510–4520.

[29] A. Howard, M. Sandler, B. Chen, W. Wang, L. Chen, M. Tan, G. Chu, V. Vasudevan, Y. Zhu, R. Pang, H. Adam, and Q. Le, "Searching for mobilenetv3," in *2019 IEEE/CVF International Conference on Computer Vision (ICCV)*, 2019, pp. 1314–1324.

[30] X. Zhang, X. Zhou, M. Lin, and J. Sun, "Shufflenet: An extremely efficient convolutional neural network for mobile devices," in *2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2018, pp. 6848–6856.

[31] F. N. Iandola, M. W. Moskewicz, K. Ashraf, S. Han, W. J. Dally, and K. Keutzer, "Squeezenet: Alexnet-level accuracy with 50x fewer parameters and $<$1mb model size," *CoRR*, vol. abs/1602.07360, 2016. [Online]. Available: http://arxiv.org/abs/1602.07360

Authorized licensed use limited to: IEEE Xplore. Downloaded on September 17,2020 at 14:54:29 UTC from IEEE Xplore. Restrictions apply.