Regular paper

SVM on Top of Deep Networks for Covid-19 Detection from Chest X-ray Images

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Abstract

In this study, we propose training a support vector machine (SVM) model on top of deep networks for detecting Covid-19 from chest X-ray images. We started by gathering a real chest X-ray image dataset, including positive Covid-19, normal cases, and other lung diseases not caused by Covid-19. Instead of training deep networks from scratch, we fine-tuned recent pre-trained deep network models, such as DenseNet121, MobileNet v2, Inception v3, Xception, ResNet50, VGG16, and VGG19, to classify chest X-ray images into one of three classes (Covid-19, normal, and other lung). We propose training an SVM model on top of deep networks to perform a nonlinear combination of deep network outputs, improving classification over any single deep network. The empirical test results on the real chest X-ray image dataset show that deep network models, with an exception of ResNet50 with 82.44%, provide an accuracy of at least 92% on the test set. The proposed SVM on top of the deep network achieved the highest accuracy of 96.16%.

Index Terms: Covid-19, X-ray image, Deep learning, Support vector machines

I. INTRODUCTION

The first case of coronavirus disease (Covid-19) was identified in Wuhan, China, at the end of December 2019 [1-4]. Covid-19 has rapidly spread to 225 countries and territories and has become an epidemic worldwide, with more than six million deaths (6,184,360) and 494,287,348 cases of infections as on April 6, 2022 (World Health Organization, https://www.who.int). Currently, real-time polymerase chain reaction (RT-PCR) is an effective method for coronaviruses diagnosis. However, the major disadvantages of RT-PCR [5-9] are its time-consuming nature and false-negative to confirm Covid-19 patients. In contrast, diagnostic imaging techniques such as chest radiography (CXR) or computed tomography

(CT) can play a crucial role in rapidly approving positive Covid-19 patients.

Deep learning techniques have been widely used in automatic medical image analysis and have shown promising results [10-14]. Instead of using handcrafted features (SIFT [15], HoG [16], GIST [17]) and training a support vector machine (SVM) [18], as in the classical framework [19-22] for image classification, the deep learning approach [23] simultaneously trains a visual feature extractor and a softmax classifier in a unified framework.

Researchers have proposed training deep neural networks to detect diseases using chest X-ray images. Kesim et al. [24] used convolutional neural networks (CNNs) to classify chest X-ray images into one of 12 classes. In a previous study [25],

tuberculosis images were recognized using deep and transfer learning. Chouhan et al. [26] proposed a combination of five deep-learning models using transfer learning for the detection of pneumonia from X-ray images. Rajpurkar et al. [27] developed a CNN architecture called CheXNeXt for classifying X-ray images into 14 different pathologies. A modified AlexNet was proposed by Bhandary et al. [28] to recognize lung abnormalities in X-ray images. Wozniak et al. [29] illustrated the incorporation of local variance analysis and probabilistic neural networks for the classification of lung carcinomas. Papers [30,31] proposed fine-tuning Inception v3 [32], Xception [33], and VGG16 [34] to identify pneumonia images.

Recently, deep learning approaches have been applied to recognize Covid-19 X-ray images. Capsule networks, namely COVID-CAPS, were proposed by Afshar et al. [35] for detecting Covid-19 images. COVIDX-Net [36] used deep network models, such as VGG19 [34], DenseNet121 [37], Inception v3 [32], ResNet v2 [38], Inception-ResNet v2, Xception [33], and MobileNet v2 [39] to classify Covid-19 x-ray images. In [40], AlexNet [41] and a modified AlexNet were applied for detection of Covid-19 from X-ray and CT images. COVID-Net was designed by Wang et al. [42] for identifying Covid-19 from X-ray images. COVIDiagnosis-Net [43] combines SqueezeNet [44] and Bayesian optimization to classifying Covid-19 images. Other studies [45,46] proposed the use of ResNet [38], Inception v3 [32], Inception-ResNet v2, MobileNet v2 [39], and SqueezeNet [44] to recognize Covid-19 X-ray images. Akkus et al. [47] evaluated the effectiveness of deep learning architectures for the automatic diagnosis of Covid-19. Enireddy et al. [48] trained the linear SVM classifier on deep features extracted by ResNet50, in other word the linear SVM substitutes for the softmax in deep networks. This study proposes to train an SVM model on top of whole deep networks.

We are interested in training a SVM [18] model on top of deep networks to detect Covid-19 from chest X-ray images. For this purpose, we gathered a real chest X-ray image dataset from public data sources [49-53] tagged in one of three classes (positive Covid-19, normal cases, and lung disease not caused by Covid-19). Subsequently, we propose to fine-tune different pre-trained deep network models, such as DenseNet121 [37], MobileNet v2 [39], Inception v3 [32], Xception [33], ResNet50 [38], VGG16, and VGG19 [34], to classify chest X-ray images. Then, we propose to train an SVM [18] on top of these deep network models to improve chest X-ray image classification. The numerical test results show that deep network models achieve an accuracy of at least 92% on the test set of real chest X-ray images (except ResNet50 with 82.44%). The proposed SVM on top of the deep networks yielded the highest accuracy of 96.16%.

The remainder of this paper is organized as follows. Section II illustrates the proposed SVM on top of the deep network models for Covid-19 detection from chest X-ray images. Section III shows the experimental results. The conclusions and future work are presented in Section IV.

II. METHODS

A. Chest x-ray Image Dataset

We started by gathering a real chest X-ray image dataset from public data sources [49-53]. The X-ray images were tagged in one of three classes (positive Covid-19 infected patients, normal cases, and lung diseases not caused by Covid-19, such as lung opacity and viral pneumonia). An example of the chest X-ray images of the three classes are shown in Fig. 1.
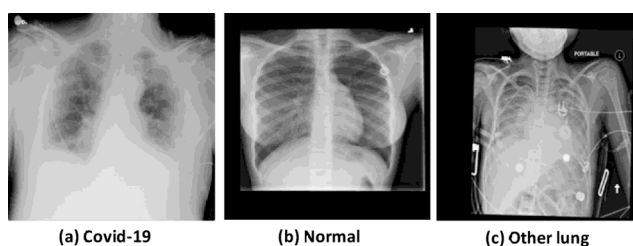

(a) Covid-19   **(b) Normal**   **(c) Other lung**

Fig. 1. Sample of chest x-ray images.

We obtained a dataset with 19,282 chest X-ray images in the PNG format, as shown in Table 1. The full dataset was randomly split into a training set (15,427 images) and a test set (3,855 images).

Table 1. Description of chest X-ray image dataset

Dataset	Covid-19	Normal	Other lung	Total
Full dataset	6,722	6,719	5,841	19,282
Trainset	5,366	5,301	4,760	15,427
Testset	1,356	1,418	1,081	3,855

B. Fine-tuning Deep Networks

In recent years, deep learning networks have focused on classifying images owing to their high accuracy. Recent deep networks, such as DenseNet121 [37], MobileNet v2 [39], Inception v3 [32], Xception [33], ResNet50 [38], and VGG [34], have achieved high classification accuracy for the ImageNet dataset [54]. Therefore, we studied these deep networks for the classification of chest X-ray images.

Instead of training deep networks from scratch, we propose fine-tuning pre-trained deep network models, such as DenseNet121, MobileNet v2, Inception v3, Xception, ResNet50, VGG16, and VGG19, to recognize Covid-19 from chest X-ray images. This approach, referred to as transfer learning [55,56], involves re-using knowledge from pre-trained deep network

models on the ImageNet dataset and performing a similar task, that is, chest X-ray image classification with a new dataset. We used the training set to fine-tune the weights of the last layers while freezing the weights of the first layers in the deep networks. We identified the best fine-tuned configurations, as listed in Table 2, for classifying chest X-ray images.

Table 2. Best fine-tuned configurations for pre-trained deep network

No	Deep network	Number of fine-tuned last layers
1	DenseNet121	20
2	MobileNet v2	8
3	Inception v3	143
4	Xception	39
5	ResNet50	14
6	VGG16	15
7	VGG19	17

C. Training Support Vector Machines on Top of Deep Networks

Any deep network model causes errors in terms of bias and variance in the image classification. Therefore, our aim was to
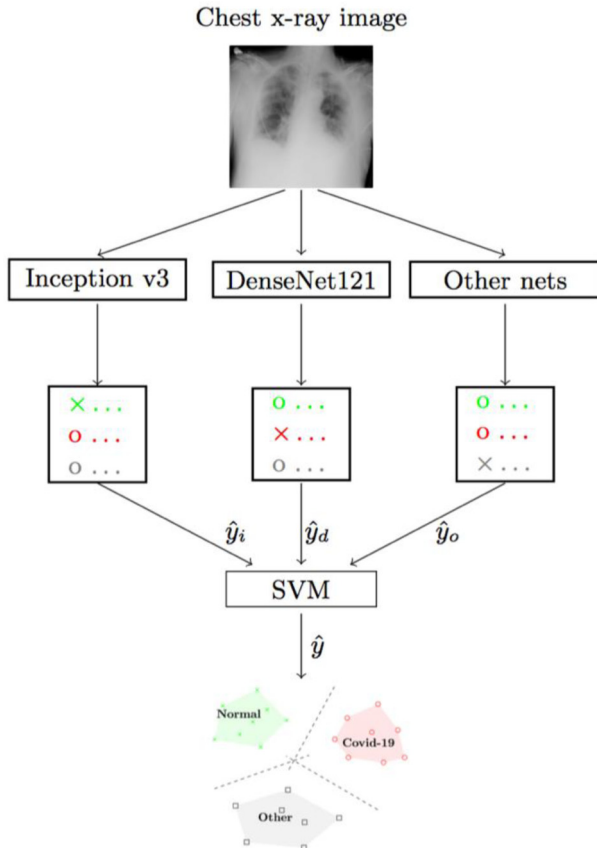

Fig. 2. Training SVM on top of deep networks for classifying chest x-ray images.

combine the strengths of deep networks to improve the classification of chest X-ray images. We proposed to train a nonlinear support vector machine model (SVM [18]) on top of seven deep network models (DenseNet121, MobileNet v2, Inception v3, Xception, ResNet50, VGG16, and VGG19), thereby complementing these single models. The proposed SVM on top of deep networks (illustrated in Fig. 2) performs a nonlinear combination of deep network outputs $\hat{y}_i$, $\hat{y}_d$, ..., $\hat{y}_o$ with a kernel function RBF (Radial Basis Function), making the prediction output $\hat{y}$. This improved the classification accuracy compared to any single deep network.

III. RESULTS

We are interested in a numerical test to assess the classification performance of the proposed SVM on top of deep networks (denoted by SVM-on-Top) in the classification of chest X-ray images.

A. Experimental Setup

First, we implemented the training programs in Python using libraries, such as Keras [57], with backend Tensorflow [58], Scikit-learn [59], and OpenCV [60].

All experiments were launched on a Linux Fedora 34 machine, Intel(R) Core i7-4790 CPU, 3.6 GHz, 4 cores, 16 GB main memory, and the Gigabyte GeForce RTX 2080Ti 11GB GDDR6, 4352 CUDA cores.

As described in Section II.A, the full X-ray image dataset was randomly divided into training (15,427 images) and test sets (3,855 images).

We used the training set to fine-tune the pre-trained DenseNet121, MobileNet v2, Inception v3, Xception, ResNet50, VGG16, and VGG19 with the best configurations, as illustrated in Table 2, learning rate = 0.001, and number of epochs = 200. The training set is used to determine the best hyper-parameters (with $\gamma = 0.2$ for the non-linear RBF kernel function and the positive constant cost = 10^5 for a trade-off between the margin size and errors) for the SVM model on top of deep networks.

For the training set, DenseNet121, MobileNet v2, Inception v3, Xception, ResNet50, VGG16, VGG19, and SVM-on-Top provided overall accuracies of 96.88, 95.31, 96.88, 96.88, 87.5, 96.88, 96.88, and 100%, respectively. Then, the resulting models were used to report the classification results on the test set.

B. Classification Results

The classification results of the deep network models and SVM on top of the deep networks are presented in Table 3 and Fig. 3. In Table 3, the highest accuracy is bold-faced, and the

second highest is in italics.

The last column of Table 3 and Fig. 3(d) present the overall accuracy of classification models. The comparison among the models illustrates that our proposed SVM-on-Top achieves the highest classification accuracy of 96.16%. SVM-on-Top resulted in improvements of 13.72, 3.84, 2.13, 1.79, 1.24, 1.17, and 0.60% for fine-tuned ResNet50, MobileNet v2, DenseNet121, VGG19, VGG16, Xception, and Inception v3, respectively.

The Covid-19 classification is shown in more detail in the third column of Table 3 and Fig. 3(a). The SVM-on-Top yielded the highest accuracy of 99.93%. Xception ranks second with 99.04%, followed by Inception v3, VGG16, VGG19, DenseNet121, MobileNet v2, and ResNet50.

Table 3. Classification accuracy on the test set (%)

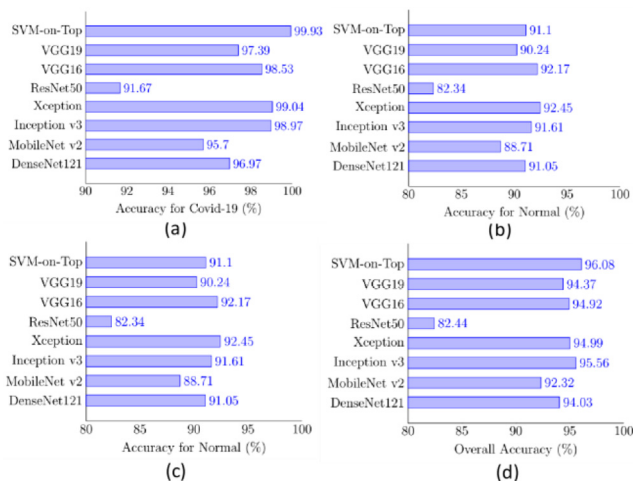| No	Model	Covid-19	Normal	Other lung	Overall
1	DenseNet121	96.97	91.05	94.10	94.03
2	MobileNet v2	95.70	88.71	92.64	92.32
3	Inception v3	98.97	91.61	96.48	95.56
4	Xception	99.04	92.45	93.23	94.99
5	ResNet50	91.67	82.34	74.46	82.44
6	VGG16	98.53	92.17	93.39	94.92
7	VGG19	97.39	90.24	96.07	94.37
8	SVM-on-Top	99.93	91.10	96.57	96.16

Fig. 3. Comparison between classification results.

The classification results of healthy lung (Normal) in the fourth column of Table 3 and Fig. 3(b) show that the highest accuracy was 92.45% performed by Xception and the second highest was 92.17% obtained by VGG16. ResNet50 exhibited the lowest accuracy (82.34 %).

Classification results for other lungs (lung opacity and viral pneumonia) as presented in the fifth column of Table 3 and Fig. 3(c) show that SVM-on-Top achieved the highest classifi-

cation accuracy of 96.57%. Inception v3 was the second most accurate model (96.48%), followed by VGG19, DenseNet121, VGG16, Xception, MobileNet v2, and ResNet50.

The computational complexity of the SVM for our proposed SVM-on-Top is squared with the number of training data points. In this training set, the learning task of SVM takes 0.25 s.

IV. CONCLUSIONS AND FUTURE WORK

We have proposed a non-linear combination of deep network outputs obtained by training an SVM model on top of deep networks for detecting Covid-19 from chest X-ray images. We gathered the chest X-ray image dataset from public data sources, including positive Covid-19, normal cases, and other lung diseases not caused by Covid-19. Recent pre-trained deep network models, such as DenseNet121, MobileNet v2, Inception v3, Xception, ResNet50, VGG16, and VGG19, were fine-tuned to classify chest X-ray images. We proposed training an SVM model on top of these fine-tuned deep networks to improve chest X-ray image classification. The proposed SVM-on-Top improved 13.72, 3.84, 2.13, 1.79, 1.24, 1.17, and 0.60% classification accuracy against fined-tuned ResNet50, MobileNet v2, DenseNet121, VGG19, VGG16, Xception, and Inception v3, respectively.

In the near future, we intend to enlarge the chest X-ray image dataset to improve the training of deep networks. A promising research aim is to select good network models for use in combination with SVM.

REFERENCES

[1] C. Huang, Y. Wang, X. Li, L. Ren, J. Zhao, Y. Hu, L. Zhang, G. Fan, J. Xu, X. Gu, Z. Cheng, T. Yu, J. Xia, Y. Wei, W. Wu, X. Xie, W. Yin, H. Li, M. Liu, Y. Xiao, H. Gao, L. Guo, J. Xie, G. Wang, R. Jiang, Z. Gao, Q. Jin, J. Wang, and B. Cao, "Clinical features of patients infected with 2019 novel coronavirus in wuhan, china," The Lancet, vol. 395, no. 10223, pp. 497-506, Feb. 2020. DOI: 10.1016/S0140-6736(20)30183-5.

[2] Q. Li, X. Guan, P. Wu, X. Wang, L. Zhou, Y. Tong, R. Ren, K. S. M. Leung, E. H. Y. Lau, J. Y. Wong, X. Xing, N. Xiang, Y. Wu, C. Li, Q. Chen, D. Li, T. Liu, J. Zhao, M. Liu, W. Tu, C. Chen, L. Jin, R. Yang, Q. Wang, S. Zhou, R. Wang, H. Liu, Y. Luo, Y. Liu, G. Shao, H. Li, Z. Tao, Y. Yang, Z. Deng, B. Liu, Z. Ma, Y. Zhang, G. Shi, T. T. Y. Lam, J. T. Wu, G. F. Gao, B. J. Cowling, B. Yang, G. M. Leung, and Z. Feng, "Early transmission dynamics in Wuhan, China, of novel coronavirus-infected pneumonia," *New England Journal of Medicine*, vol. 382, pp. 1199-1207, Mar. 2020. DOI: 10.1056/NEJMoa2001316.

[3] F. Wu, S. Zhao, B. Yu, Y. Chen, W. Wang, Z. Song, Y. Hu, Z. Tao, J. Tian, Y. Pei, M. Yuan, Y. Zhang, F. Dai, Y. Liu, Q. Wang, J. Zheng, L. Xu, E. C. Holmes, and Y. Zhang, "A new coronavirus associated with human respiratory disease in China," *Nature*, vol. 579, pp. 1-8, Feb. 2020. DOI: 10.1038/s41586-020-2008-3.

[4] N. Zhu, D. Zhang, W. Wang, X. Li, B. Yang, J. Song, X. Zhao, B. Huang, W. Shi, R. Lu, P. Niu, F. Zhan, D. Wang, W. Xu, G. Wu, G. F. Gao, D. Phil., and W. Tan, "A novel coronavirus from patients with pneumonia in China, 2019," *New England Journal of Medicine*, vol. 382, pp. 727-733, Feb. 2020. DOI: 10.1056/NEJMoa2001017.

[5] I. Arevalo-Rodriguez, D. Buitrago-Garcia, D. Simancas-Racines, P. Zambrano-Achig, R. D. Campo, A. Ciapponi, O. Sued, L. Martines-Garcia, A. W. Rutjes, N. Low, P. M. Bossuyt, J. A. Perez-Molina, and J. Zamora, "False-negative results of initial rt-pcr assays for covid-19: A systematic review," *PLoS One*, vol. 15, no. 12, p. e0242958, Dec. 2020. DOI: 10.1371/journal.pone.0242958.

[6] J. F. Chan, S. Yuan, K. Kok, K. K. To, H. Chu, J. Yang, F. Xing, J. Liu, C. C. Yip, R. W. Poon, H. Tsoi, S. K. Lo, K. Chan, V. K. Poon, W. Chan, J. D. Ip, J. Cai, Y. C. Cheng, H. Chen, C. K. Hui, and K. Yuen, "A familial cluster of pneumonia associated with the 2019 novel coronavirus indicating person-to-person transmission: A study of a family cluster," *The Lancet*, vol. 395, no. 10223, pp. 514-523, Feb. 2020. DOI: 10.1016/S0140-6736(20)30154-9.

[7] W. Hao and M. Li, "Clinical diagnostic value of CT imaging in COVID-19 with multiple negative RT-PCR testing," *Travel Medicine and Infectious Disease*, vol. 34, p. 101627, Mar.-Apr. 2020. DOI: 10.1016/j.tmaid.2020.101627.

[8] P. Huang, T. Liu, L. Huang, H. Liu, M. Lei, W. Xu, X. Hu, J. Chen, and B. Liu, "Use of chest ct in combination with negative RT-PCR assay for the 2019 novel coronavirus but high clinical suspicion," *Radiology*, vol. 295, no. 1, pp. 22-23, Apr. 2020. DOI: 10.1148/radiol.2020200330.

[9] X. Xie, Z. Zhong, W. Zhong, W. Zhao, C. Zheng, F. Wang, and J. Liu, "Chest CT for typical coronavirus disease 2019 (COVID-19) pneumonia: Relationship to negative RT-PCR testing," *Radiology*, vol. 296, no. 2, pp. E41-E45, Feb. 2020. DOI: 10.1148/radiol.2020200343.

[10] Z. Akkus, A. Galimzianova, A. Hoogi, D. L. Rubin, and B. J. Erickson, "Deep learning for brain MRI segmentation: State of the art and future directions," *Journal of Digital Imaging*, vol. 30, no. 4, pp. 449-459, Jun. 2017. DOI: 10.1007/s10278-017-9983-4.

[11] J. Ker, L. Wang, J. Rao, and T. Lim, "Deep learning applications in medical image analysis", *IEEE Access*, vol. 6, pp. 9375-9389, Dec. 2017. DOI: 10.1109/ACCESS.2017.2788044.

[12] C. Liang, Y. Liu, M. Wu, F. Garcia-Castro, A. Alberich-Bayarri, and F. Wu, "Identifying pulmonary nodules or masses on chest radiography using deep learning: External validation and strategies to improve clinical practice," *Clinical Radiology*, vol. 75, no. 1, pp. 38-45, Jan. 2020. DOI: 10.1016/j.crad.2019.08.005.

[13] G. Litjens, T. Kooi, B. E. Bejnordi, A. A. A. Setio, F. Ciompi, M. Ghafoorian, J. A. W. M. van der Laak, B. van Ginneken, and C. I. Sanchez, "A survey on deep learning in medical image analysis," *Medical Image Analysis*, vol. 42, pp. 60-88, Dec. 2017. DOI: 10.1016/j.media.2017.07.005.

[14] D. Shen, G. Wu, and H. Suk, "Deep learning in medical image analysis," *Annual Review of Biomedical Engineering*, vol. 19, pp. 221-248, Jun. 2017. DOI: 10.1146/annurev-bioeng-071516-044442.

[15] D. G. Lowe, "Distinctive image features from scale-invariant keypoints," *International Journal of Computer Vision*, vol. 60, pp. 91-110, Nov. 2004. DOI: 10.1023/B:VISI.0000029664.99615.94.

[16] N. Dalal and B. Trigs, "Histograms of oriented gradients for human detection," in *Proceedings of the 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, San Diego: CA, USA, pp. 886-893, 2005. DOI: 10.1109/CVPR.2005.177.

[17] A. Oliva and A. Torralba, "Modeling the shape of the scene: A holistic representation of the spatial envelope," International Journal of Computer Vision, vol. 42, pp. 145-175, May. 2001. DOI: 10.1023/A:1011139631724.

[18] V. N. Vapnik, *The Nature of Statistical Learning Theory*, 2nd ed. Springer-Verlag, 2000.

[19] A. Bosch, A. Zisserman, and X. Munoz, "Scene classification via plsa," in *Proceedings of the European Conference on Computer Vision*, Graz, Austria, pp. 517-530, 2006. DOI: 10.1007/11744085_40.

[20] T. Do, P. Lenca, and S. Lallich, "Classifying many-class high-dimensional fingerprint datasets using random forest of oblique decision trees," *Vietnam Journal of Computer Science*, vol. 2, pp. 3-12, Jun. 2014. DOI: 10.1007/s40595-014-0024-7.

[21] L. Fei-Fei and P. Perona, "A bayesian hierarchical model for learning natural scene categories," in *2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, San Diego: CA, USA, pp. 524-531, 2005. DOI: 10.1109/CVPR.2005.16.

[22] Sivic and Zisserman, "Video Google: A text retrieval approach to object matching in videos," in *9th IEEE Intl Conference on Computer Vision*, Nice, France, vol. 2, pp. 1470-1477, 2003. DOI: 10.1109/ICCV.2003.1238663.

[23] Y. Lecun, L. Bottou, Y. Bengio, and P. Haffner, "Gradient-based learning applied to document recognition," in *Proceedings of the IEEE*, vol. 86, no. 11 pp. 2278-2324, Nov. 1998. DOI: 10.1109/5.726791.

[24] E. Kesim, Z. Dokur, and T. Olmez, "X-ray chest image classification by a small-sized convolutional neural network," in *2019 Scientific Meeting on Electrical-Electronics Biomedical Engineering and Computer Science (EBBT)*, Istanbul, Turkey, pp. 1-5, 2019. DOI: 10.1109/EBBT.2019.8742050.

[25] C. Liu, Y. Cao, M. Alcantara, B. Liu, M. Brunette, J. Peinado, and W. Curioso, "TX-CNN: Detecting tuberculosis in chest x-ray images using convolutional neural network," in *2017 IEEE Intl Conference on Image Processing (ICIP)*, Beijing, China, pp. 2314-2318, 2017. DOI: 10.1109/ICIP.2017.8296695.

[26] V. Chouhan, S. K. Singh, A. Khamparia, D. Gupta, P. Tiwari, C. Moreira, R. Damasevicius, and V. H. C. de Albuquerque, "A novel transfer learning based approach for pneumonia detection in chest X-ray images," *Applied Sciences*, vol. 10, no. 2, p. 559, Jan. 2020. DOI: 10.3390/app10020559.

[27] P. Rajpurkar, J. Irvin, R. L. Ball, K. Zhu, B. Yang, H. Mehta, T. Duan, D. Ding, A. Bagul, C. P. Langlotz, B. N. Patel, K. W. Yeom, K. Shpanskaya, F. G. Blankenberg, J. Seekins, T. J. Amrhein, D. A. Mong, S. S. Halabi, E. J. Zucker, A. Y. Ng, and M. P. Lungren, "Deep learning for chest radiograph diagnosis: A retrospective comparison of the CheXNeXt algorithm to practicing radiologists," *PLOS Medicine*, vol. 15, no. 11, p. e1002686, Nov. 2018. DOI: 10.1371/journal.pmed.1002686.

[28] A. Bhandary, G. A. Prabhu, V. Rajinikanth, K. P. Thanaraj, S. C. Satapathy, D. E. Robbins, C. Shasky, Y. Zhang, J. M. R. S. Tavares, and N. S. M. Raja, "Deep-learning framework to detect lung abnormality - A study with chest X-ray and lung CT scan images," Pattern Recognition Letters, vol. 129, pp. 271-278, Jan. 2020. DOI: 10.1016/j.patrec.2019.11.013.

[29] M. Wozniak, D. Polap, G. Capizzi, G. L. Sciuto, L. Kosmider, and K. Frankiewicz, "Small lung nodules detection based on local variance analysis and probabilistic neural network," *Computer Methods and Programs in Biomedicine,* vol. 161, pp. 173-180, Jul. 2018. DOI: 10.1016/j.cmpb.2018.04.025.

[30] E. Ayan and H. M. Unver, "Diagnosis of pneumonia from chest X-ray images using deep learning," in *2019 Scientific Meeting on Electrical-Electronics & Biomedical Engineering and Computer Science (EBBT)*, Istanbul, Turkey, pp. 1-5, 2019. DOI: 10.1109/

EBBT.2019.8741582.

[31] S. S. Yadav and S. M. Jadhav, "Deep convolutional neural network based medical image classification for disease diagnosis," *Journal of Big Data*, vol. 6, p. 113, Dec. 2019. DOI: 10.1186/s40537-019-0276-2.

[32] C.L Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna, "Rethinking the inception architecture for computer vision," *arXiv:1512.00567*, 2015. DOI: CoRR abs/1512.00567.

[33] F. Chollet, "Xception: Deep learning with depthwise separable convolutions," *arXiv:1610.02357*, 2016. DOI: CoRR abs/1610. 02357.

[34] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," *arXiv:1409.1556*, 2014. DOI: CoRR abs/1409.1556.

[35] P. Afshar, S. Heidarian, F. Naderkhani, A. Oikonomou, K. N. Plataniotis, and A. Mohammadi, "COVID-CAPS: A capsule network-based framework for identification of COVID-19 cases from X-ray images," *Pattern Recognition Letters*, vol. 138, pp. 638-643, Oct. 2020. DOI: 10.1016/j.patrec.2020.09.010Get rights and content.

[36] E. E. Hemdan, M. A. Shouman, and M. E. Karar, "COVIDX-Net: A framework of deep learning classifiers to diagnose COIVD-19 in X-ray images, *arXiv:2003.11055*, 2020. DOI: 10.48550/arXiv.2003. 11055.

[37] G. Huang, Z. Liu, L. V. D. Maaten, and K. Q. Weinberger, "Densely connected convolutional networks," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, Honolulu: HI, USA, pp. 2261-2269, 2017.

[38] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," *CoRR abs/1512.03385*, 2015. DOI: 10.48550/arXiv.1512.03385.

[39] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L. Chen, "MobileNetV2: Inverted residuals and linear bottlenecks," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, Salt Lake City: UT, USA, pp. 4510-4520, 2018.

[40] H. S. Maghdid, A. T. Asaad, K. Z. Ghafoor, A. S. Sadiq, and M. K. Khan, "Diagnosing COIVD-19 pneumonia from X-ray and CT images using deep learning and transfer learning algorithms," *arXiv:2004.00038*, p. 26, 2021. DOI: 10.48550/arXiv.2004.00038.

[41] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet classification with deep convolutional neural networks," *Communication of the ACM*, vol. 60, no. 6, pp. 84-90, Jun. 2017. DOI: 10.1145/3065386.

[42] L. Wang, Z. Q. Lin, and A. Wong, "COVID-Net: A tailored deep convolutional neural network design for detection of COIVD-19 cases from chest X-ray images," *Scientific Reports*, vol. 10, p. 19549, Nov. 2020. DOI: 10.1038/s41598-020-76550-z.

[43] F. Ucar and D. Korkmaz, "COVIDiagnosis-Net: Deep bayes-squeezenet based diagnosis of the coronavirus disease 2019 (COIVD-19) from X-ray images," *Medical Hypotheses*, vol. 140, p. 109761, Jul. 2020. DOI: 10.1016/j.mehy.2020.109761.

[44] F. N. Iandola, S. Han, M. W. Moskewicz, K. Asraf, W. J. Dally, and K. Keutzer, "SqueezeNet: AlexNet-level accuracy with 50x fewer parameters and <0.5MB model size," *arXiv:1602.07360*, 2016. DOI: 10.48550/arXiv.1602.07360.

[45] A. Narin, C. Kaya, and Z. Pamuk, "Automatic detection of coronavirus disease (COVID-19) using X-ray images and deep convolutional neural networks, *Pattern Analysis and Applications*, vol. 24, no. 3, pp. 1207-1220, May. 2021. DOI: 10.1007/s10044-021-00984-y.

[46] M. Togacar, B. Ergen, and Z. Comert, "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, Jun. 2020. DOI: 10.1016/j.compbiomed.2020.103805.

[47] I. D. Apostolopoulos and T. A. Mpesiana, "Covid-19: Automatic detection from X-ray images utilizing transfer learning with convolutional neural networks," *Physical and Engineering Sciences in Medicine*, vol. 43, no. 2, pp. 635-640, Apr. 2020. DOI: 10.1007/s13246-020-00865-4.

[48] V. Enireddy, M. J. K. Kumar, B. Donepudi, and C. Karthikeyan, "Detection of COVID-19 using hybrid ResNet and SVM," in *Proceedings of IOP Conference Series: Materials Science and Engineering*, Kancheepuram, India, vol. 993, no. 1, 2020.

[49] 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: 2006.11988*, 2020. DOI: 10.48550/arXiv.2006.11988.

[50] A. Haghanifa, M. M. Majdabadi, and S. Ko, "COVID-19 chest X-ray image repository," May. 2021. DOI: 10.6084/m9.figshare.12580328.v3.

[51] H. B. Winther, H. Laser, S. Gerbel, S. K. Maschke, J. B. Hinrichs, J. Vogel-Claussen, F. K. Wacker, M. M. Hoper, and B. C. Meyer, "Dataset: Covid-19 image repository," 2020.

[52] M. de la Iglesia Baya, J. M. Saborit, J. A. Montell, A. Pertusa, A. Bustos, M. Cazorla, J. Galant, X. Barber, D. Orozco-Beltran, F. Garcia-Garcia, M. Caparros, G. Gonzalez, and J. M. Salinas, "BIMCV COVID-19+: A large annotated dataset of RX and CT images from COVID-19 patients," arXiv:2006.01174v3, 2021. DOI: 10.48550/arXiv.2006.01174.

[53] D. S. Kermany, M. Goldbaum, W. Cai, C. C. S. Valentim, H. Liang, S. L Baxter, A. McKeown, G. Yang, X. Wu, F. Yan, J. Dong, M. K. Prasadha, J. Pei, M. Y. L. Ting, J. Zhu, C. Li, S. Hewett, J. Dong, I. Ziyar, A. Shi, R. Zhang, L. Zheng, R. Hou, W. Shi, X. Fu, Y. Duan, V. A. N. Huu, C. Wen, E. D. Zhang, C. L. Zhang, O. Li, X. Wang, M. A. Singer, X. Sun, J. Xu, A. Tafreshi, M. A. Lewis, H. Xia, and K. Zhang, "Identifying medical diagnoses and treatable diseases by image-based deep learning," *Cell*, vol. 172, no. 5, pp. 1122-1131.e9, Feb. 2018. DOI: 10.1016/j.cell.2018.02.010.

[54] J. Deng, A. C. Berg, K. Li, and L. Fei-Fei, "What does classifying more than 10,000 image categories tell us?," in *Computer Vision - ECCV 2010 - 11th European Conference on Computer Vision*, Heraklion, Crete, Greece, pp. 71-84, 2010. DOI: 10.1007/978-3-642-15555-0_6.

[55] A. S. Razavian, H. Azizpour, J. Sullivan, and S. Carlsson, "CNN features off-the-shelf: An astounding baseline for recognition," in *IEEE Conference on Computer Vision and Pattern Recognition, CVPR Workshops 2014*, Columbus: OH, USA, pp. 512-519, 2014.

[56] J. Yosinski, J. Clune, Y. Bengio, and H. Lipson, "How transferable are features in deep neural networks?," in *Advances in Neural Information Processing Systems 27 (NIPS 2014)*, Montreal: QC, Canada, pp. 3320-3328, 2014.

[57] Keras (2015) [Online]. Available: https://keras.io.

[58] M. Abadi, A. Agarwal, P. Barham, E. Brevdo, Z. Chen, C. Citro, G. Corrado, A. Davis, J. Dean, M. Devin, S. Ghemawat, I. Godfellow, A. Harp, G. Irving, M. Isard, Y. Jia, R. Jozefowicz, L. Kaiser, M. Kudlur, J. Levenberg, D. Mane, R. Monga, S. Moore, D. Murray, C. Olah, M. Schuster, J. Shlens, B. Steiner, I. Sutskever, K. Talwar, P. Tucker, V. Vanhoucke, V. Vasudevan, F. Viegas, O. Vinyals, P. Warden, M. Wattenberg, M. Wicke, Y. Yu, and X. Zheng, "TensorFlow: Large-scale machine learning on heterogeneous distributed systems," *arXiv:1603.04467v2*, 2015. DOI: 10.48550/arXiv.1603.04467.

[59] F. Bedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J.

Vanderplas, A. Passos, D. Cournapeau, M. Brucher, and E. Duchesnay, "Scikit-learn: Machine learning in python," *Journal of Machine Learning Research*, vol. 12, no. 85, pp. 2825-2830, 2011.

[60] Itseez: Open-source computer vision library. (2015) [Online]. Available: https://github.com/opencv/opencv.

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