Accuracy Improvement in Detection of COVID-19 in Chest Radiography

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***Abstract*—From late 2019 to early 2020, the coronavirus outbreak affected 213 countries and territories around the world. This respiratory virus seriously affects human lung functionality. One way to diagnose this illness and find out if the lungs are infected is to evaluate chest X-ray. The evaluation of X-rays is challenging because corona has minor effects on the lungs in the early stages, and other diseases can have a similar effect. In this condition, Computer-Aided Diagnosis (CAD) can make a huge contribution and help decision support for healthcare professionals. Deep learning has obtained great results in data analysis recently, but the requirement for a large amount of training data prevents the use deep learning in medical data analysis since it is difficult to obtain a large amount of data from the medical field. This paper proposes an effective deep transfer learning-based model that improves current state-of-the-art systems in COVID-19 detection in chest radiographs. The weights of the DesneNet121 and ResNet50 on the Imagenet have transferred as initial weights, and then the two models have been fine-tuned with a deep classifier with data augmentation to detect three classes of COVID-19, Viral Pneumonia and normal radiographs. The proposed models obtained 97.83% accuracy with minimal false-negative results on the only public available COVID-19 radiography dataset. The Image-Level Accuracy (ILA) of the results outperform the results of previous studies, together with sensitivity and recall performance. Moreover, the proposed methods are scalable, and can be expanded to cover the detection of other types of diseases in the future and be integrated with more CNNs to increase their generalization capabilities.**

***Index Terms*—COVID-19, CNN, DensNet, ResNet, COVID-19 Radiography database, Medical image classification, Computer-Aided Diagnosis (CAD)**

I. Introduction

As a new respiratory virus, corona shocked the world with its high infection rate. People in Wuhan city in China were the first group that faced this phenomenon in December 2019 and in short windows after the whole world has been being challenged by the corona pandemic. It is conceded that the virus has transmitted from mammals to human [1]. World Health Organization announced the pandemic of this virus known as COVID-19 [2] [3] .Researches are showing that there are dozens of viruses contain coronavirus family, but seven types of them can be fatal. The healthcare system was not ready for this sudden growth in COVID-19 patients. As a result, there are not enough diagnosis kits, hospital beds for admission of patients, ventilators, and personal protective equipment (PPE) for healthcare personnel. In response to the sudden outbreak of COVID-19, extensive Research and Development have been performing actively to find an effective diagnostic way or vaccination. The research field is not limited to the medical field and contains various fields such as biotechnology, data science, and artificial intelligence to provide useful analysis, technical solutions, and Computer-Aided Diagnosis (CAD). Since the COVID-19 invades mainly to human lungs, it is important for healthcare professionals to find out whether the lungs are already invaded or no. This can be crucial to prioritize patients' illness levels and the need for hospitalization. It is proven that the novel COVID-19 enters through the humans' respiratory tract, affects the lungs critically, and causes severe pneumonia. The lung gets inflamed, becomes filled with fluids, and develops patches called Ground-Glass Opacity (GGO). Following the fact that symptoms of the disease are hard to recognize, and there is a debate about the effectiveness of testing kits, there is a need for new methods of diagnosis [4]. One of the main methods of finding out the lung engagement of COVID-19 is chest radiography. This chest x-ray analysis is, however, challenging since some types of pneumonia and illness can affect the lungs, and the diagnosis process becomes difficult. One method that can alleviate the mentioned challenges is Computer-Aided Diagnosis (CAD). It is proven that Convolutional Neural Networks (CNN) are effective in image processing [5]. This work focuses on the automatic detection of COVID-19 in chest radiography images.

This work aims to develop a high accuracy method that can detect COVID-19 at early stages, define the exact type of the samples, and improve previous works results. Achieving a high accuracy result helps the feasibility of CAD systems for COVID-19 recognition in medical practice.

II. Related Works

Nowadays, data science has help medical data analysis breakthrough and application of deep learning has been increased for medical diagnosis and decision support in various medical fields [6] [3] [7] [8] [9] [10].Study [11] has used support vector machine (SVM), random forest, K-Nearest

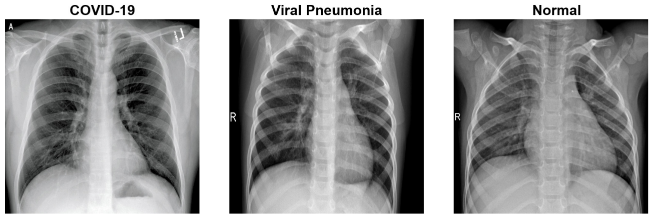

Fig. 1. A sample of COVID-19, Viral Pneumonia, and Normal x-ray of human chest.

neighbor (KNN), and CNN with softmax classifier. IN [10], a ReLU based deep learning approach is used to malignant lung cancer. This study achieved an accuracy of 85.5%. Research [12] trained ResNet23 and ResNet18 on CT scan images and obtained 86.7% accuracy. In [13], the trend of COVID-19 has been evaluated from John Hopkins Univesity dataset. Study [14] has used a UNet++ deep learning model on 51 patients with positive COVID-19 test result in Wuhan. This study doesn't provide any information about the dataset size and availability of it. Similarly, the study [15] introduced a deep learning method to detect COVID-19 and achieved an accuracy of 73.1%. This method, however, needs manual marking of the region of interest of COVID-19 illness. They used a dataset related to 99 patients in which there were 55 cases of pneumonia and 44 cases of COVID-19. In [16], a dataset of 618 medical images was trained by a ResNet23 deep learning-based network and obtained an accuracy of 86.7%. Research [17] proposed a neural network which is made from a concatenation of Xception and ResNet50 network. Figure 2 shows the architecture of this model. It utilizes multiple features that are extracted by two networks. This study has trained its model on 11302 images and achieved an average accuracy of 91.4%.

In [18], a Cascade-SEMEnet which combines ResNet50 and DenseNet169 is proposed. Each of these two cascaded parts adopts a large input size uses histogram equalization in order to increase data. First, chest X-rays are screened by the ResNet50 part to diagnose three classes of normal, bacterial, and viral pneumonia. Then, the DenseNet169 part is used for fine-grained classification of Viral Pneumonia. Finally, Viral Pneumonia cases are further analyzed to detect COVID-19 samples. In order to eliminate the effect of non-pathological features on the network, data with the U-Net method is used for the training of the DenseNet169 part of the network. This method gained 85.6% accuracy in the determination of pneumonia types and 97% in fine-grained classification of COVID-19 on a dataset of more than 5000 X-ray images.

Study [19] proposed a deep learning approach for detection COVID-19 from non-COVID-19 images. They have used multiple CNN models such as AlexNet, VGG, SqueezeNet, GoogleNet. They achieved their best results with Xception and ResNet-101 on CT scan images from 194 patients. Research [20] proposed an object detection architecture and trained it on a dataset of 1500 images of infected, non-infected, and pneumonia images. The aim was to classify data as negative and positive COVID-19 samples. It obtained 94.9% of sensibility and 92.0% of specificity in COVID-19 detection. In [21], three networks (ResNet50, Inception V3, and Inception-ResNet v2) were considered and trained on chest X-ray radiographs and stated that ResNet and Inception v3 work better than Inception-ResNet v2. The study used a deep learning model to conduct features of medical images and classify them through exploiting the SVM classifier. This method obtained 95% accuracy. In [22], a weakly-supervised deep learning model was developed by the use of 3D CT volumes to detect COVID-19. Figure 3 represents this architecture. In each sample, the lung region was segmented by using a pre-trained UNet. Moreover, the segmented region was used for training a 3D deep neural network. This method achieved 90.7% sensitivity and 90% accuracy for predicting positive COVID-19 samples.

Research [23] proposed a deep learning network called DarkCOVIDNet with an end-to-end structure without a need for manual feature extraction. Figure 4 illustrates this system. It ends with average pooling and a Softmax classifier to encounter the classification of images with subtle details. It achieved an accuracy of 87.0% in multiclass classification (COVID vs. No-Findings vs. Pneumonia).

III. CHALLENGES

Since COVID-19 is a new phenomena, researches and advancements related to this virus are in their infant level. Therefore, COVID-19 related datasets are highly limited in variety of samples, mostly non-public, and very small. At the time being there is only one public COVID-19 X-ray dataset available called COVID-19 Radiography Database [24]. Unfortunately, some GDPR challenges prevent researchers from sharing their data. Having said that, COVID-19 Radiography database contains only 219 COVID-19 positive images, together with 1341 normal images and 1345 viral pneumonia images, has been chosen for our experiments. This small dataset makes the classification task very challenging since machine learning methods requires far more amount of input data for a perfect training [25]. Furthermore, there is not any information about the number of patients in which this dataset are gathered from them. So it is not possible to calculate Patient-level Accuracy (PLA) of trained models.

IV. SYSTEM MODEL

In general, when training a network with a standard optimization algorithm, as long as the number of layers increases, the training error decreases in the beginning, but after a moment it starts increasing. So, in deep networks, the training error is worse than a shallow one. However, if a highly accurate model is desired, there is a need for having a deep network [26]. Intermediate hidden layers in a deep model can help taking out features of input data while a shallow models doesn't have such an ability [27].
On the other hand, if we have a deep network, the problem of vanishing gradient descent prevents the use of deep networks during training and back propagation. The unique structure

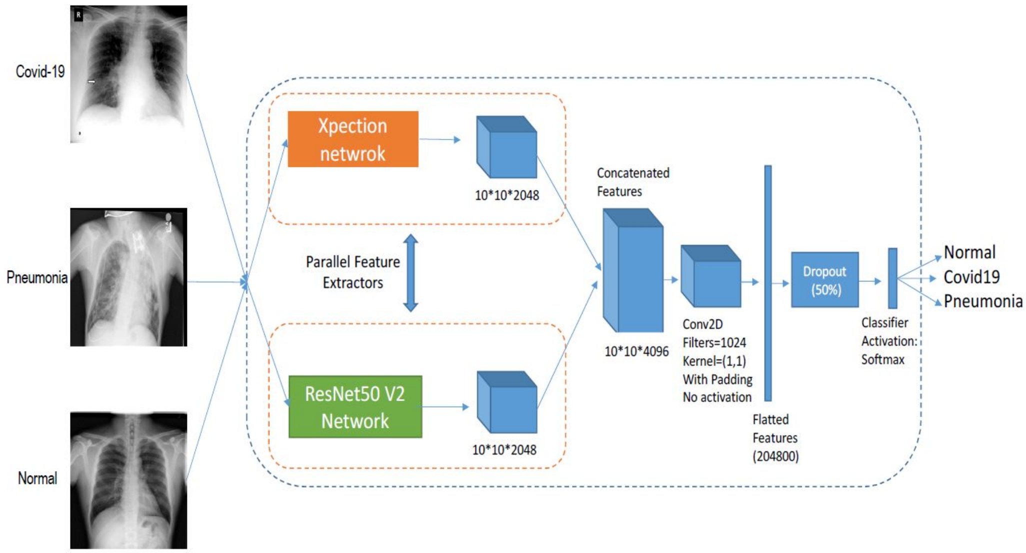

Fig. 2. concatinated ResNet50 and Xception architecture [17].

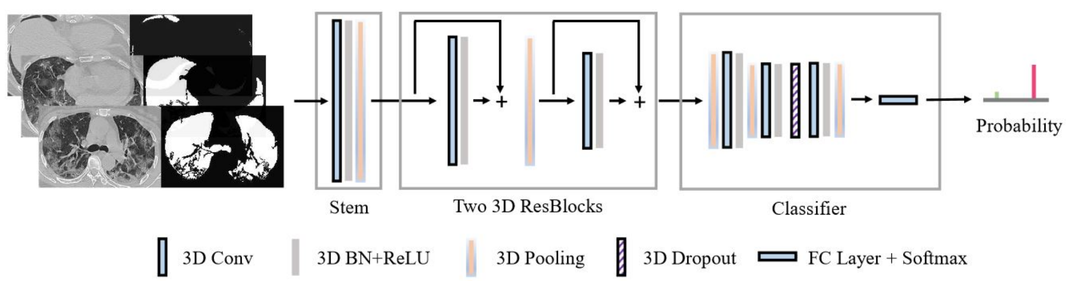

Fig. 3. Architecture of the DeCoVNet proposed in [22] . The network takes a CT volume with its 3D lungmask as input data and outputs the probabilities of COVID-positive and negative.

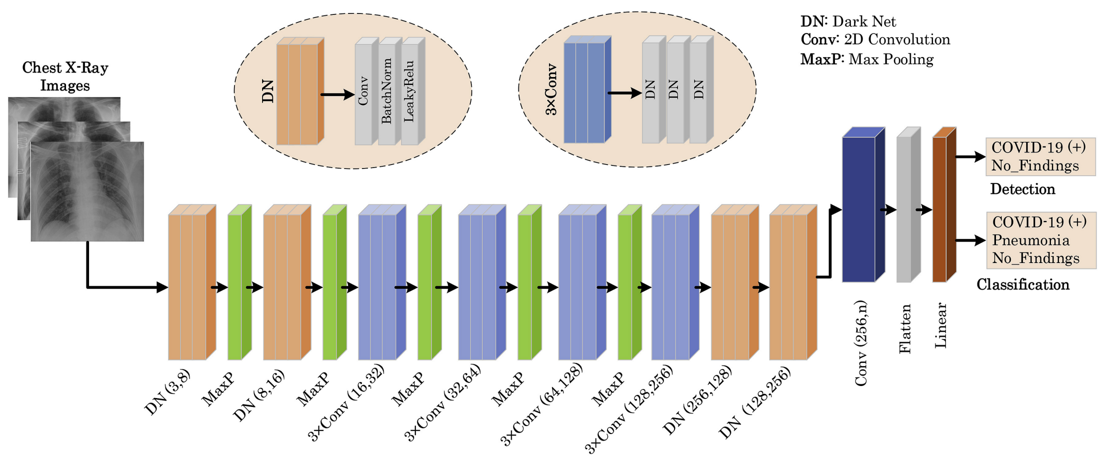

Fig. 4. Architecture of DarkCovidNet [23].

of ResNet and DensNet networks are somehow avoiding the vanishing gradient descent problem. ResNet network is made of residual blocks. In plain networks, every layer is connected to the next layer but in a network with the residual building blocks, every block not only is connected into the next layer, but it has shortcut connections into the next layer. Figure 5 represents a residual block. First, the input data x goes through a few convolutional layers (function $f(x)$) same as a plain. Then the ResNet brings the original input data x to the result ($f(x)$), so the output becomes $f(x) + x$. This is an element-wise addition ($\oplus$). In fact, the information in x finds a shortcut to go deeper into the neural network and we can have more layers without vanishing gradient descent [26] [28] [29] [30] [31].

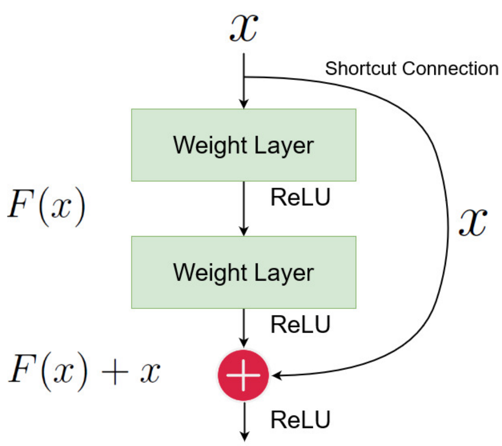

Fig. 5. A residual block

ResNet50 has five segments. Every segment consists of a residual block together with a convolutional block. Residual blocks are having three convolutional blocks, and each convolutional block has three convolutional layers. ResNet50 has approximately 23 million parameters.

Another solution for having a deep effective network is using a DenseNet base model. In DenseNet, each layer has additional inputs from previous layers. DenseNet has a feature layer, multiple dense blocks, and a few transition layers among dense blocks [32].

The intermediate activations in DenseNet avoid vanishing gradient problems; Therefore, as the number of layers increases and the network is getting deeper, training error keeps going down.

V. Implementation and Results

A. Dataset Partitioning

Since the dataset is not large enough for a thorough training, the partitioning process is considered. We have divided the dataset into train, validation, and test set with 1778 (61%), 712 (25%), and 415 (14%) images, respectively.

B. Data Augmentation

Every image in the training set is first resized to 224x224 pixels. Then some of the images horizontally flipped randomly. We then colorjittered images for training and validation. The training set images are rotated and cropped randomly. Finally, the images are transformed into tensors. As for the validation set, all images were just normalized. The test set is given to the trained model just after resizing the image to the models required input size without any edition (raw image).

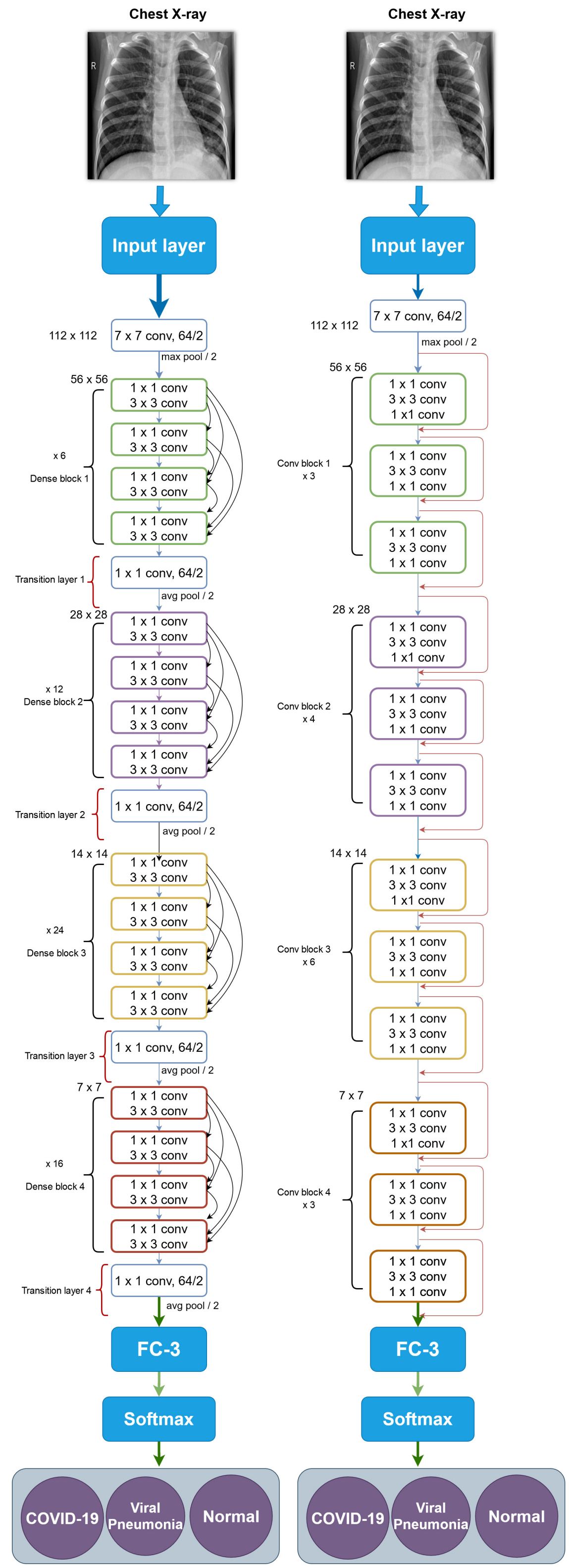

Fig. 6. Proposed model's structure. DensNet based model (left), and ResNet based model (right).

C. Hyperparameters Optimization and Settings

A set of hyperparameters and settings for our specific task are defined and experimented. Table I shows these optimized hyperparameters and settings.

TABLE I
HYPERPARAMETERS AND SETTINGS

Hyperparametrs and settings	**Setting Range**		**Optimized Setting**
$learningrate(\alpha)$	0.00002	0.2	0.002
γ	0.1	0.9	0.9
$momentum$	0.1	0.9	0.9
$stepsize$	1	2	2
$batchsize$	4	64	16
$inputsize$	100×100	229×229	224×224
$epochs$	50	200	200
$lossfunction$	Cross-Entropy	Hinge Loss	Cross-Entropy

D. Hardware and Software Requirements

The proposed model has been implemented on a desktop with the specification given in the table II.

TABLE II
HARDWARE CONFIGURATION

Specs	**Configuration**
OS	Windows 10- 64bit
CPU	Intel(R) Core(TM) i5-6600 CPU @ 3.30GHz 3.31Ghz
GPU	NVIDIA 1060 - 6 GB memory
RAM	16 GB

As for software, we have used PyTorch in the Jupyter Notebook of Anaconda environment.

E. Results

The proposed models have been trained and tested. The results of the experiments are shown in the tables III and IV. The confusion matrix of experiments are also provided in figures 7 and 8 for better evaluation of the results

TABLE III
RESNET BASED MODEL'S RESULT

Metric	**Accuracy**
ILA	97.83%
Precision	100%
Recall	96.80%
$F1_{score}$	98.37%

TABLE IV
DENSENET BASED MODEL'S RESULT

Metric	**Accuracy**
ILA	97.83%
Precision	100%
Recall	94.06%
$F1_{score}$	96.93%

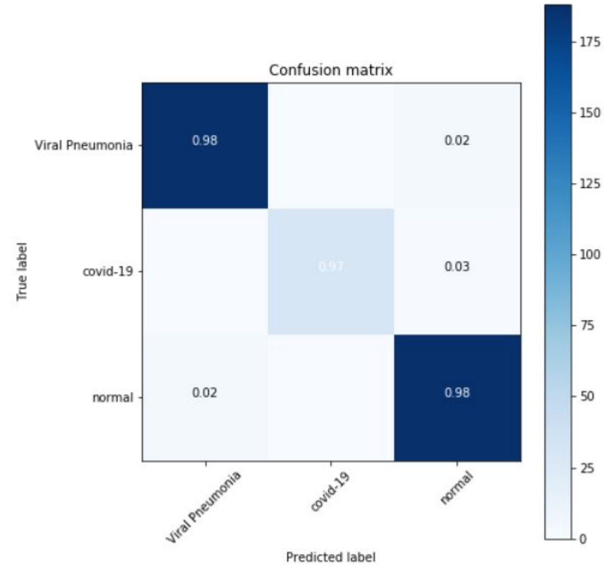

Fig. 7. Confusion matrix of ReseNet based model

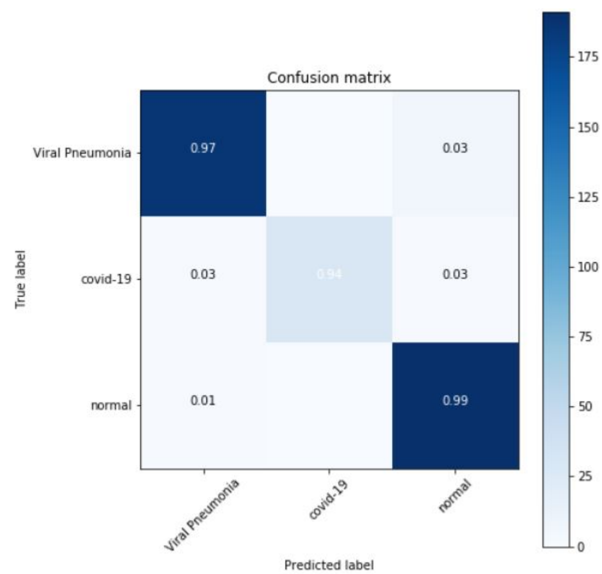

Fig. 8. Confusion matrix of DenseNet based model

VI. Conclusion

To sum up, we found out that because the dataset is small, the pre-trained network is able to provide the best accuracies. The process of choosing the best pre-trained network is, nevertheless, challenging. The ResNet50 and DenseNet121 are chosen for this specific problem because they are improving in the time span in the training process due to their specific structure (shortcuts). This research utilizes DenseNet121 CNN for the classification in this specific task for the first time. Previous works have implemented ResNet, VGG, and AlexNet for their model. Our results showing that it is feasible to create high accuracy system for COVID-19 diagnosis without having a large dataset. We achieved the accuracy of 97.83%, 100%, 96.80%, and 98.37% for ILA, precision, recall and $F1_{score}$, respectively. Our results are improving state-of-the-art results accuracies. The proposed model is designed to be flexible, and it is possible to combine it with other models to have a bigger model to boost the performance of the CAD system.

VII. Future Work

The dataset was small, which makes the data diversity extremely limited. The proposed model is showing promising results, but before using it in real-world examples, it has to be trained and tested with a few a larger datasets to increase the variety of data.

Moreover, the proposed model needs to be improved in false-negative results, which is a very key aspect of a CAD system. Another future study can be combining resnet and densenet and train it as a unique system to evaluate the results.

References

[1] Y. Fan, K. Zhao, Z.-L. Shi, and P. Zhou, "Bat coronaviruses in china," *Viruses*, vol. 11, no. 3, p. 210, 2019.

[2] H. Iqbal, K. D. Romero-Castillo, M. Bilal, and R. Parra-Saldivar, "The emergence of novel-coronavirus and its replication cycle: an overview," *J Pure Appl Microbiol*, vol. 14, no. 1, pp. 13–16, 2020.

[3] M. K. Siddiqui, R. Morales-Menendez, P. K. Gupta, H. Iqbal, F. Hussain, K. Khatoon, and S. Ahmad, "Correlation between temperature and covid-19 (suspected, confirmed and death) cases based on machine learning analysis," *J Pure Appl Microbiol*, vol. 14, 2020.

[4] Y. Xie, X. Wang, P. Yang, and S. Zhang, "Covid-19 complicated by acute pulmonary embolism," *Radiology: Cardiothoracic Imaging*, vol. 2, no. 2, p. e200067, 2020.

[5] F. A. Spanhol, L. S. Oliveira, P. R. Cavalin, C. Petitjean, and L. Heutte, "Deep features for breast cancer histopathological image classification," in *2017 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*. IEEE, 2017, pp. 1868–1873.

[6] M. K. Siddiqui, M. Z. Islam, and M. A. Kabir, "A novel quick seizure detection and localization through brain data mining on ecog dataset," *Neural Computing and Applications*, vol. 31, no. 9, pp. 5595–5608, 2019.

[7] F. Shan, Y. Gao, J. Wang, W. Shi, N. Shi, M. Han, Z. Xue, and Y. Shi, "Lung infection quantification of covid-19 in ct images with deep learning," *arXiv preprint arXiv:2003.04655*, 2020.

[8] E. Klang, "Deep learning and medical imaging," *Journal of thoracic disease*, vol. 10, no. 3, p. 1325, 2018.

[9] L. O. Hall, R. Paul, D. B. Goldgof, and G. M. Goldgof, "Finding covid-19 from chest x-rays using deep learning on a small dataset," *arXiv preprint arXiv:2004.02060*, 2020.

[10] G. A. P. Singh and P. Gupta, "Performance analysis of various machine learning-based approaches for detection and classification of lung cancer in humans," *Neural Computing and Applications*, vol. 31, no. 10, pp. 6863–6877, 2019.

[11] T. Ozcan, "A deep learning framework for coronavirus disease (covid-19) detection in x-ray images," 2020.

[12] C. Butt, J. Gill, D. Chun, and B. A. Babu, "Deep learning system to screen coronavirus disease 2019 pneumonia," *Applied Intelligence*, p. 1, 2020.

[13] D. Fanelli and F. Piazza, "Analysis and forecast of covid-19 spreading in china, italy and france," *Chaos, Solitons & Fractals*, vol. 134, p. 109761, 2020.

[14] J. Chen, L. Wu, J. Zhang, L. Zhang, D. Gong, Y. Zhao, S. Hu, Y. Wang, X. Hu, B. Zheng *et al.*, "Deep learning-based model for detecting 2019 novel coronavirus pneumonia on high-resolution computed tomography: a prospective study," *MedRxiv*, 2020.

[15] S. Wang, B. Kang, J. Ma, X. Zeng, M. Xiao, J. Guo, M. Cai, J. Yang, Y. Li, X. Meng *et al.*, "A deep learning algorithm using ct images to screen for corona virus disease (covid-19)," *MedRxiv*, 2020.

[16] X. Xu, X. Jiang, C. Ma, P. Du, X. Li, S. Lv, L. Yu, Q. Ni, Y. Chen, J. Su *et al.*, "A deep learning system to screen novel coronavirus disease 2019 pneumonia," *Engineering*, 2020.

[17] M. Rahimzadeh and A. Attar, "A new modified deep convolutional neural network for detecting covid-19 from x-ray images," *arXiv preprint arXiv:2004.08052*, 2020.

[18] D. Lv, W. Qi, Y. Li, L. Sun, and Y. Wang, "A cascade network for detecting covid-19 using chest x-rays," *arXiv preprint arXiv:2005.01468*, 2020.

[19] 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.

[20] F. A. Saiz and I. Barandiaran, "Covid-19 detection in chest x-ray images using a deep learning approach," *International Journal of Interactive Multimedia and Artificial Intelligence, InPress (InPress)*, p. 1, 2020.

[21] A. Narin, C. Kaya, and Z. Pamuk, "Automatic detection of coronavirus disease (covid-19) using x-ray images and deep convolutional neural networks," *arXiv preprint arXiv:2003.10849*, 2020.

[22] C. Zheng, X. Deng, Q. Fu, Q. Zhou, J. Feng, H. Ma, W. Liu, and X. Wang, "Deep learning-based detection for covid-19 from chest ct using weak label," *medRxiv*, 2020.

[23] 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*, p. 103792, 2020.

[24] T. R. Kaggle, "Covid-19 radiography database," https://www.kaggle.com/tawsifurrahman/covid19-radiography-database/data, 2020.

[25] R. Miotto, F. Wang, S. Wang, X. Jiang, and J. T. Dudley, "Deep learning for healthcare: review, opportunities and challenges," *Briefings in bioinformatics*, vol. 19, no. 6, pp. 1236–1246, 2018.

[26] Y. Yari, T. V. Nguyen, and H. T. Nguyen, "Deep learning applied for histological diagnosis of breast cancer," *IEEE Access*, vol. 8, pp. 162 432–162 448, 2020.

[27] J. Ba and R. Caruana, "Do deep nets really need to be deep?" in *Advances in neural information processing systems*, 2014, pp. 2654–2662.

[28] C. Szegedy, S. Ioffe, V. Vanhoucke, and A. A. Alemi, "Inception-v4, inception-resnet and the impact of residual connections on learning," in *Thirty-first AAAI conference on artificial intelligence*, 2017.

[29] L. Wen, X. Li, and L. Gao, "A transfer convolutional neural network for fault diagnosis based on resnet-50," *Neural Computing and Applications*, pp. 1–14, 2019.

[30] K. He, X. Zhang, S. Ren, and J. Sun, "Identity mappings in deep residual networks," in *European conference on computer vision*. Springer, 2016, pp. 630–645.

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

[32] G. Huang, Z. Liu, 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, pp. 4700–4708.