



(RESEARCH ARTICLE)



Automatically identify COVID-19 and Pneumonia patients using Deep learning in Chest X-rays image

Md Haris Uddin Sharif ^{1,*} and Shaamim Udding Ahmed ²

¹ School of Computer and Information Sciences, University of the Cumberland, Williamsburg, Kentucky, USA.

² Strayer University, Silver Spring, Maryland, USA.

World Journal of Advanced Research and Reviews, 2021, 12(03), 011-019

Publication history: Received on 28 October 2021; revised on 30 November 2021; accepted on 02 December 2021

Article DOI: <https://doi.org/10.30574/wjarr.2021.12.3.0662>

Abstract

At the end of 2019, a new kind of coronavirus (SARS-CoV-2) suffered worldwide and has become the pandemic coronavirus (COVID-19). The outbreak of this virus led to crisis around the world and kills millions of people globally. On March 2020, WHO (World Health Organization) declared it as pandemic disease. The first symptom of this virus is identical to flu and it destroys the human respiratory system. For the identification of this disease, the first key step is the screening of infected patients. The easiest and most popular approach for screening of the COVID-19 patients is chest X-ray images. In this study, our aim to automatically identify the COVID-19 and Pneumonia patients by the X-ray image of infected patient. To identify COVID-19 and Pneumonia disease, the convolution Neural Network was training on publicly available dataset on GitHub and Kaggle. The model showed the 98% and 96% training accuracy for three and four classes respectively. The accuracy scores showed the robustness of both model and efficiently deployment for identification of COVID-19 patients.

Keywords: COVID-19; X-ray imaging; Convolutional neural networks; Feature extraction; Pneumonia Diseases; Deep learning; Lung

1. Introduction

In 2019 of December, COVID-19 first instance was affirmed in Wuhan the city of China. Within a brief period of 2 months the confirmed cases rose to 1000, having nearly 6000 suspects of having disease. The novel disease had covered the world by September 2020 with an increase in confirmed number of cases regularly. Coronavirus is an infection that causes serious respiratory ailments going from the normal cold to hazardous illnesses. At beginning of the epidemic, people had no idea about the virus. People had no idea about coronavirus in the beginning of epidemic. As per China National Health Commission's "COVID-19 Diagnosis and Treatment Plan for Pneumonia infections caused by Bat Illness (Trial Version 5)" and Dr. Zhong's explanation of this virus pandemic. It incorporates more than 85% similitudes and identifies with practically a similar family but are not precisely the same [1].

Academician Zhong Nanshan and his team submitted a report on the characteristics of COVID-19 on February 9, 2020 [2]. Investigating clinical examples from 1099 positive cases yielded various clinical highlights about the COVID disease, accentuating the patient's essential symptoms and radiological elements.

Primary symptoms of the virus, by WHO reports, are comparable to those of the regular flu: sickness, fatigue, chronic cough, breathlessness, joint pain, and hoarseness [3]. The similarity of COVID-19 symptoms to flu signs makes timely identification of the coronavirus difficult. COVID-19, like other viruses and bacteria, has been believed to cause bronchitis in some patients, and the care for COVID-19 Pneumonia differs from that for other respiratory contagions.

* Corresponding author: Haris Uddin Sharif

School of Computer and Information Sciences, University of the Cumberland, Williamsburg, Kentucky, USA.

Furthermore, patients with bacterial Pneumonia necessitate antibiotic treatment, whilst patients with bronchiolitis can be treated with intensive care [4]. As a result, correct scrutiny of COVID-19 is important for saving humanoid lives and halting the global epidemic outbreak.

In moreover to an incubation time of isolating for 14 days, the COVID-19 Diagnosis and Treatment Strategy by the National Health Commission [5]. Medical practitioners oftenly employ chest X-ray scanning to confirm or eliminate the chances of a bronchitis infection. COVID-19 steadily expands lungs density, which can lead to severe life-threatening acute pulmonary disease [6]. Main image aberrations such as lateral lines, or ventral changes, as well as ground glass occlusion, can be seen on a COVID-19 chest X-ray image [7].

As a result, this imaging method used as a first-line diagnostic instrument for COVID-19 detection by looking for continual aesthetic irregularities in a patient's chest X-ray image [8]. Even though imaging techniques give better resolution, the chest X-ray image is expensive and sensitive [9][10]. In the unavailability of diagnostic kits and screening sites, the widespread accessibility of X-ray machineries makes it a promising option for COVID-19 identification. Yet, manual evaluation of every X-ray image and retrieval of the results is the most difficult aspect of an X-ray-based COVID-19 method for the determination. This would necessitate a significant amount of time and the participation of medical personnel. Evaluation techniques are required to recognize positive cases of the disease from their X-rays. In generating high quality results deep learning approach is known for its effectiveness, as well as other benefits including: (1) optimum use of large datasets, (2) removal of added expenses, (3) reduce feature, (4) elimination of manual data annotation. As a result, recent deep learning models are frequently employed to retrieve important attributes and characteristics from the pictures in categories them using their independent nature. Deep learning algorithms have, in fact, made a substantial contribution to the diagnosis of diseases and the development of outstanding classification performance with far less time-taking modeled tasks [4]. To detect COVID-19, the suggested technique employs a deep learning method via the ChestNet algorithm, which yields promising results.

2. Literature Review

In previous times, convolution neural networks were constructed using deep learning models, which has resulted in numerous breakthroughs in object detection, recognition, and segmentation of images. It is feasible to design end-to-end models that gain knowledge from the data and find classification patterns in it across a number of processing layers by eliminating the need to extract features separately through deep learning artificial intelligence. The rapid expansion of the COVID-19 disease outbreak has compelled the creation of novel approaches to meet the outbreak's increasing healthcare demands.

In the literature [11], there are many conventional deep learning convolution neural networks deployed to detect COVID-19 with and without modifications in the design [12]. In the wide range of research fields and disciplines these models have been used for object detection and image identification. Among the most widely utilized algorithms, some locational production models are VGG-16/19, AlexNet, GoogleNet, and LetNet. Depth-based CNNs, such as MobileNet, ResNet, Inception-V3, V4. (3) DenseNet, Xception, SqueezeNet, as well as other models are examples. Deep transfer learning can be used to pre-train these architectures [13]. [14].

In preliminary research on COVID-19, Shan et al introduced a versatile framework dependent on profound learning for characterization and quantitative examination to explore the chest (CT) of the infectious ailing region and the total respiratory framework design and man-machine circle effectiveness label each case. In Tianjin Medical University's Cancer Hospital, Wang et.al developed a theoretical foundation to analyze the COVID-19. The created model extracted features of COVID-19 images to analyze positive cases [15]. [16].

To properly identify COVID-19 patients, specialists from Huazhong University of Science and Technology's Affiliated Hospital utilized three-dimensional computer tomography (CT) and neural network based supervised deep learning to identify coronavirus bronchitis to categories both negative and positives cases of the disease [17].

In Birmingham City University and Arthurs University, researchers like Asmaa and Mohammad used coronavirus pneumonia images for its classification and identification through the convolutional neural network as well as class decomposition method for analyzing its class boundaries to cope with any anomalies in the dataset, focusing for high accessibility of COVID-19 named dataset [18].

Li studied affirmed instances of COVID-19 patients by using their chest tomography (CT) through deep CNNs [19]. Rehman et.al utilized pre trained models' information to fabricate a coordinated identification system to figure out how COVID-19 affected role from bronchiolitis and healthy individuals [20]. As the pandemic has advanced, machine and

deep learnings have been utilized to recognize patients of COVID-19. Wang et.al detected COVID-19 through chest computer tomography using inception network [16].

Asif et.al in [21] utilized the inception V3 algorithm demonstrating its ease of implementation and reliability of detecting COVID-19 by the images of chest x-rays of the patients and implementing transfer learning method. Pre-trained model of modified ResNet50 is utilized by Song et.al in [22] for efficiently categorizing healthy people, patients with COVID-19 and acute bronchitis. Loey et.al achieved 80.6% of accuracy in detecting and classifying patients with COVID-19, viral Pneumonia, acute bronchitis, through a pretrained model of Google Net [23].

The authors created the combinational neural network with Xception and ResNet50V2 that properly classified patients of COVID-19 with a chest x-ray with 99.65 percent accuracy [24]. Hassanien et al. used a multi layered criterion in conjunction with a support vector machine (SVM) mechanism to accurately categorize COVID-19-infected people X-ray images [25]. Alqudah and co-author implemented the categorization of chest x rays with great precision using machine learning techniques like random forest (RF), SVM, and CNN [26]. Osi demonstrated that RF outperforms linear discriminant analysis (LDA) as well as SVM in predicting COVID-19 effects [27].

In [28] Kumar et.al incorporated DenseNet121 as well as SqueezeNet 1.0 through transfer learning and made DeQueueNet to retrieve general significance and relative effect of characteristics from X-ray images during classification procedure of COVID-19 patients. Abbas et.al modified a deep learning convolutional neural network known as transmission or also DeTrac to categorize images of chest x-ray of COVID-19 positive patients. The algorithm is a category degradation methodology for analyzing image datasets that can manage any anomalies in the boundary [18].

Having 93.48 percent efficiency, Apostolopoulos et al. established a system for multi classifying images of COVID-19 using five variants of convolutional neural network. Horry et al. detected COVID-19 using both VGG16 and VGG19 algorithms, with 80% of recall and precision [30]. Sethy and Behera anticipated a state-of-the-art deep learning technique for classifying chest X-ray images of COVID positive patients.[31]. For categorizing and extracting features, the program employs nine pre-trained frameworks and SVMs. Among which ResNet50-plus SVM's efficiency rate was better than some other models, having 95.38 percent and 95.52 percent F1-score, respectively.

With 99.01 percent accuracy, Rajaraman et al. [32] utilized recursively pruned deep learning models to categorize chest x-rays into regular, COVID-19, or acute bronchitis. Different models were assessed in order to improve the classification efficiency, through different clustering techniques models with the best results were consolidated. However, such methodologies are best suited for limited images of COVID-19 dataset, as computation complexity is very high of multiple models calculation, so with the large dataset there is no certainty that their efficiency would be maintained [33,34].

In this sense, other proposals have also been suggested using deep learning for three-class characterization. Cases are classified as COVID-19, normal, or bronchitis in research by [35-38]. Peers [39, 40] or serious intense respiratory disorder (SARS) [29] changed Pneumonia with a conventional non-COVID-19 group. In a four-class classification, experiments differentiate between bacterial and viral bronchitis less commonly [11]. Various studies [13, 14] used binary classification model to divide patients into COVID-19 positive and COVID-19 negative groups. Despite the fact that these methodologies attained high precision (more than 89 percent), the number of COVID-19 dataset is limited. For example, in [35], the dataset consisted only 45 images and used only 45 COVID-19 images. Furthermore, successive model used a subset of the same dataset for testing, which could result in erroneously enhanced effectiveness, especially since the same subject could have dataset related to various X-ray images.

3. Methodology

3.1. Dataset

The dataset of chest x-ray images for the COVID-19 classification was downloaded from GitHub. The X-ray images dataset was gathered from Kaggle (a huge source of public datasets) for the pneumonia diseases. Both datasets were merged to form a collective dataset related to COVID-19 and Pneumonia chest X-ray images. The collected dataset contains the 468 COVID-19 images and 3875 pneumonia images. Images of Pneumonia were further separated into two classes (Bacterial Pneumonia and Viral Pneumonia). Lastly, the dataset was based on four classes and the images count of each class is available in Table 1.

Table 1 Number of total images in each class of prepared dataset

Class Label	Class Name	Total images
0	Normal	1341
1	Bacterial Pneumonia	#
2	Viral Pneumonia	#
3	COVID-19	468

3.2. Preprocessing

All the images of x-ray were into gray-scale images. As the chest X-ray images dataset was composed of large images, the most significant step of preprocessing was the resizing of images. The size of all images was changed to 224 x 224 x 1 so that rational computational time can be achieved during the deep learning model training. Deep learning models required a sufficient amount of data for the reliable training and excellent result of the model. The technique of augmentation was used to increase the dataset to some reasonable amount. The vertical flip, horizontal flip, rotation, translation and blurring techniques were used to augment data. Lastly, we converted the augmented grayscale image to 3 channel images for fine tuning.

3.3. Model

For the Classification of COVID-19 and Pneumonia, the pretrained model of PyTorch (cheXNet) was used for training. CheXNet model is based on 121 convolutional layers (Dense Network of DenseNet) and trained on the 14 dataset of Chest X-rays images. Dense Net uses the pretrained weights of ImageNet and replace the fully connected layer with the single output layer. It also replaces the SoftMax function with the nonlinearity sigmoid function. The hyperparameters of the CheXNet were: optimizer=Adam, batch size=16, and learning rate=0.001 for training. The count of training and testing images is available in table 2.

Table 2 Count of X-ray images in training and testing set after augmentation

Class Label	Class Name	Total images	After Augmentation	Training	Testing
0	Normal	1341	#	#	233
1	Bacterial Pneumonia	#	#	#	242
2	Viral Pneumonia	#	#	#	148
3	COVID-19	468	#	#	30

The CheXNet pretrained model was selected as base model for training. The dataset was split into 80% and 20% into training and testing set respectively. For the training of the model on 4 classes rather than 14 classes the output layer of the model was modified. The split of 0.2% of training set was used for validation during the training of the model. The Adam optimizer with batch size 8 was used for the training of the model. Later, the model was fine-tuned by changing the learning rates and optimization algorithm. The model was tested on the best fine-tuned model by calculating the evaluation measures using Eq 1-4. In Eq 1-4, the TP, TN, FP and FN are abbreviated from true positive, true negative, false positive and false negative respectively. As the false predicted covid-19 X-ray images were more costly for our system, so the main goal of the model was to achieve the high score of recall.

4. Results

This study presented a fully automated deep learning model for the Classifying COVID-19 virus among the other viral viruses. The chest X-ray pictures of four classes, including COvid-19, Bacterial Pneumonia, and Viral Pneumonia and Normal images were gathered from Kaggle and GitHub (see methodology).

Firstly, the CheXNet pretrained model was trained on three classes (COVID-19, Pneumonia and Normal). We merged the Viral Pneumonia and Bacterial Pneumonia into single parent class and label as Pneumonia. The data set was split and 80% of it was used for training data and for testing the data, 20% of it was used. The Adam optimizer with different

learning rates was used to train the model. By comparing the evaluation scores of the model with different learning rates, model performed best with Adam optimizer on 0.001 learning rate. CheXNet showed the approximately 98% accuracy with the significant score of other evaluation measures (Table 3). The model was evaluated on testing data by plotting the confusion matrix (Figure 1). It was shown that all the COVID-19 samples are correctly classified using the confusion matrix. But for the Pneumonia images, model predicts the 2 samples of Pneumonia as Normal Chest images. The False positive and false Negative valuation of the model confirmed that the model is fair enough to deploy in real world environment. The ROC trajectory of the trained model is also presented in Figure 2.

Table 3 Evaluation scores of the CheXNet model on three classes

Class	AUROC	Sensitivity	PPV
Normal Lung	0.9788	0.761	0.989
Bacterial Pneumonia	0.9798	0.961	0.881
Viral Pneumonia	0.9370	0.872	0.721
COVID-19	0.9994	1.000	0.938

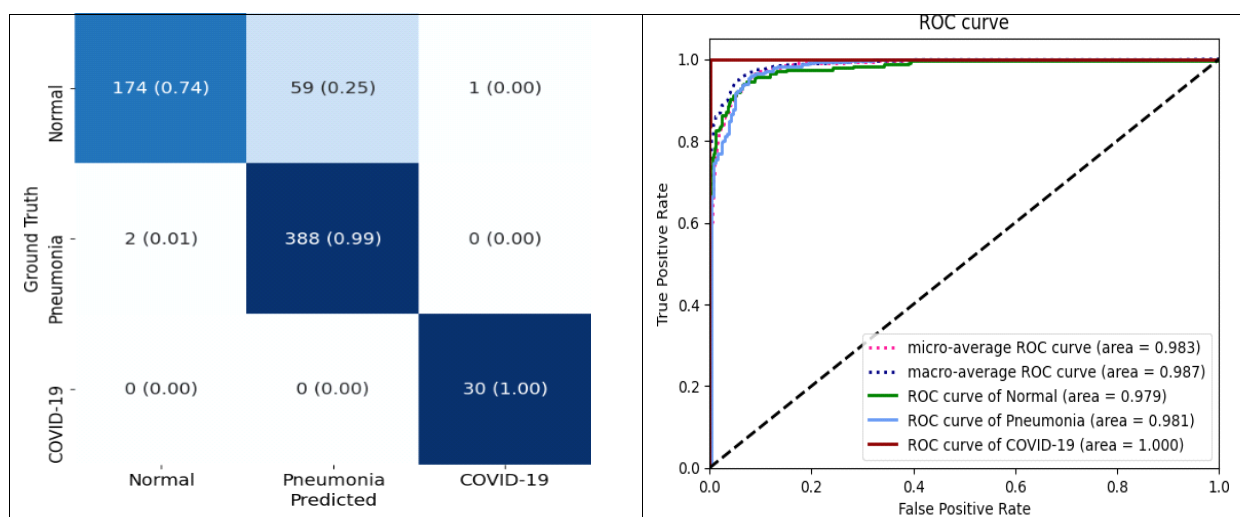


Figure 1 Confusion matrix

Secondly, the dataset with their original classes ($c=4$) was used to train the CheXNet model. Same configuration settings were followed to train the model. By the testing data, confusion matrix of the model was calculated (Figure 3). The accuracy, precision, recall and F1-Score were calculated by confusion matrix in Table 4. The confusion matrix showed that the model still correctly classified the all samples of COVID-19. While the model incorrectly classified the 18 Viral sample as Bacterial and 7 Bacterial samples as Viral. The model also wrongly classified the 18 and 43 Normal Samples as Bacterial and Viral Pneumonia samples. The significant false negative score of the model showed how robust the trained model was and made the model capable to make predictions in real world environment after clinical trials. The ROC curves of CheXNet models on four classes is also presented in Fig 4. The evaluation of both model for unseen image is also presented in Fig 5.

Table 4 Evaluation scores of the CheXNet model on four classes

Class	AUROC	Sensitivity	PPV
Normal Lung	0.9788	0.761	0.989
Bacterial Pneumonia	0.9798	0.961	0.881
Viral Pneumonia	0.9370	0.872	0.721
COVID-19	0.9994	1.000	0.938

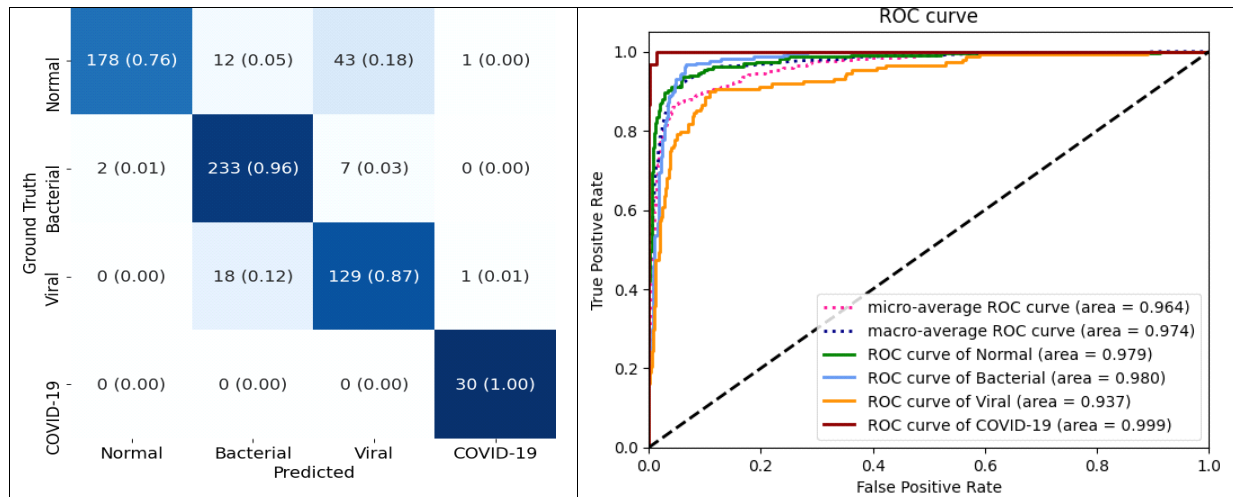


Figure 2 ROC trajectory of the trained model

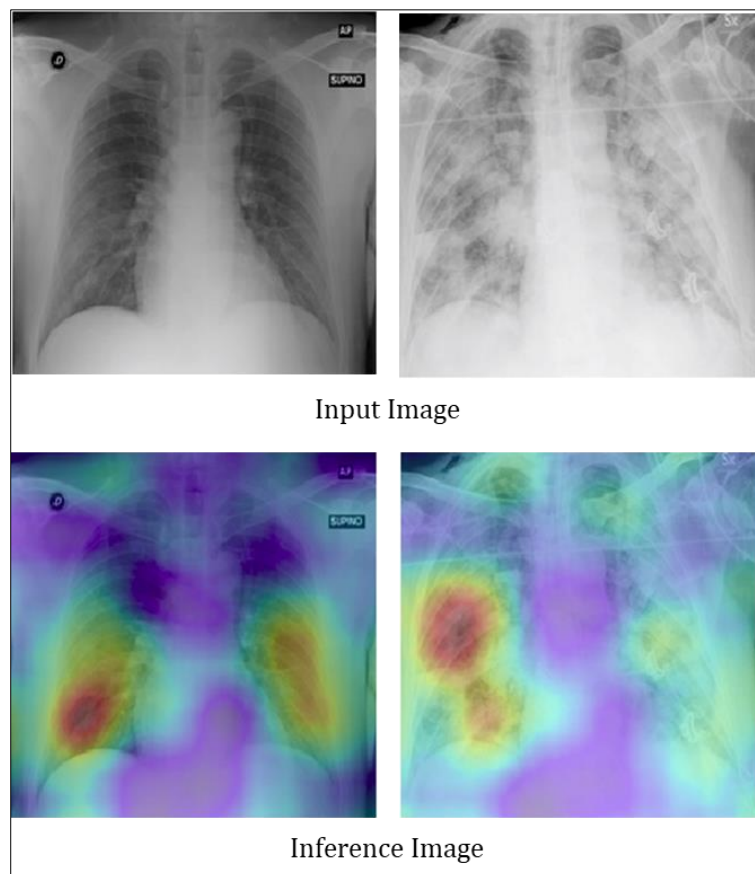


Figure 3 Calculated model

5. Discussion

In this study the transfer learning technique was used for the classification of Pneumonia and COVID-19 disease with Normal samples using Chest X-ray images. Firstly, the CheXNet model with their pretrained weights was used for the classification of Chest X-ray of three classes (Pneumonia, COVID-19, and Normal). The newly trained CheXNet model showed the significant scores for the selected evaluation measures in Table 3. But the model was unable to classify the type of Pneumonia and also classify the 59 Normal samples as pneumonia samples. It showed that the Pneumonia is the most deceptive class for the model and model hardly distinguished between Normal and Pneumonia samples. Later, it was seen that the Pneumonia class has two distinct types (Bacterial and Viral Pneumonia). Once again, the CheXNet

model with their pretrained weights was used for the categorization of Pneumonia and COVID-19 diseases on the four classes. After the training of the CheXNet model, the evaluation scores showed slightly decline on testing set. The fall of evaluation score was due to the miss classification of Normal samples. As the model was confused between normal and Pneumonia samples in the first model and predicted some wrong classification for normal class, the Pneumonia class is further divided into Bacterial and Viral classes. Now the model is more hardly distinguished between Pneumonia classes and Normal samples. That's why the model wrongly classified to Normal samples into Pneumonia classes and Pneumonias classes into Normal samples. However, for classifying patients with COVID-19 chest X-ray images, each model is robust enough to predict real-world data. For the significant Pneumonia image classification, there is a need to perform some advanced image processing steps. These steps will emphasize the affected area of Pneumonia images and distinguished them from the Normal images. Resultantly, the same models will be robust enough to make predictions for Pneumonia images.

6. Conclusion

In this study, the images from Kaggle and GitHub were used related to chest x ray of patients having Pneumonia and COVID-19. To train the model, the count of image was increase up to appropriate amount by augmentation. The resizing and scaling technique were used for the training of model in time period. The CheXNet pretrained model was used with pretrained weights. By the transfer learning technique, CheXNet model was trained on three and four classes to classify Pneumonia and COVID-19. The CheXNet model showed the 98% and 96% accuracy on the three and four classes respectively. For the COVID-19 class, model showed the accurate results. Although, the Pneumonia class was deceptive for the model and model predict some wrong classification between Pneumonia class and Normal class. However, the Pneumonia and Normal class's misclassification can be handled by performing some image processing steps in future study.

Compliance with ethical standards

Acknowledgments

The authors wish to thank Kaggle and GitHub, which provided all the datasets and images and the technical material for the performance of this study.

Disclosure of conflict of interest

All authors declare that they have no conflict of interest.

Statement of informed consent

Informed consent was obtained from all individual participants included in the study.

References

- [1] Novel Coronavirus Diagnosis and Treatment Plan for Pneumonia Infected by Bat Disease (trial version 5), 2000.
- [2] W.-j. Guan, Yu Hu, W.-h. Liang et al., Clinical Characteristics of 2019 Novel Coronavirus Infection in China, MedRxiv, Cold Spring, NY, USA, 2020.
- [3] Zhang W. Imaging changes of severe COVID-19 pneumonia in advanced stage. *Intens. Care Med.* (2020); 46(5):841–3 2. Coronavirus and pneumonia. WebMD (2020); <https://www.webmd.com/lung/covid-and-pneumonia#1>
- [4] Jain G, Mittal D, Thakur D, Mittal MK. A deep learning approach to detect COVID-19 coronavirus with X-Ray images. *Biocybern. Biomed. Eng.* (2020); 40(4):1391–405
- [5] J.-Y. Zhao, J.-Y. Yan, and J.-M. Qu, "Interpretations of "diagnosis and treatment protocol for novel coronavirus pneumonia (trial version 7)"" *Chinese Medical Journal*, vol. 133, no. 11, pp. 1347–1349, 2020.
- [6] Bressemer KK, Adams LC, Albrecht J, Petersen A, Thieb HM, Niehues SM, Vahldiek JL. Is lung density associated with severity of COVID-19? *Pol. J. Radiol.* (2020); 85: e600-606.
- [7] Cleverley J, Piper J, Jones MM. The role of chest radiography in confirming COVID-19 pneumonia. *BMJ* (2020); 370:m2426

- [8] Rubin GD, Reyerson CJ, Haramati LB, Sverzellati N, Kanne JP, Raof S, et al. The role of chest imaging in patient management during the COVID-19 pandemic: a multinational consensus statement from the Fleischner society. *Chest* (2020); 158, 106–116
- [9] Annarumma M, Withey SJ, Bakewell RJ, Pesce E, Goh V, Montana G. Automated triaging of adult chest radiographs with deep artificial neural networks. *Radiology* (2019); 291(1):196–202.
- [10] Mazurowski MA, Buda M, Saha A, Bashir MR. Deep learning in radiology: an overview of the concepts and a survey of the state of the art with focus on MRI. *J. Magn. Reson. Imaging* (2019); 49(4):939–54
- [11] Khan, A.; Sohail, A.; Zahoora, U.; Qureshi, A.S. A survey of the recent architectures of deep convolutional neural networks. *Artif. Intell. Rev.* 2020, 53, 5455–5516.
- [12] Islam, M.M.; Karray, F.; Alhaji, R.; Zeng, J. A Review on Deep Learning Techniques for the Diagnosis of Novel Coronavirus (COVID-19). *IEEE Access* 2021, 9, 30551–30572.
- [13] Sethy, P.K.; Behera, S.K.; Ratha, P.K.; Biswas, P. Detection of coronavirus Disease (COVID-19) based on Deep Features and Support Vector Machine. *Int. J. Math. Eng. Manag. Sci.* 2020, 5, 643–651.
- [14] Khan, A.I.; Shah, J.L.; Bhat, M.M. CoroNet: A deep neural network for detection and diagnosis of COVID-19 from chest x-ray images. *Comput. Methods Programs Biomed.* 2020, 196, 105581.
- [15] F. Shan, Y. Gao, J. Wang et al., “Lung infection quantification of covid-19 in ct images with deep learning,” 2020, <https://arxiv.org/abs/2003.04655>.
- [16] S. Wang, B. Kang, J. Ma et al., “A deep learning algorithm using ct images to screen for corona virus disease (COVID19),” *European Radiology*, vol. 31, 2020.
- [17] C. Zheng, Deep Learning-Based Detection for COVID-19 from Chest CT Using Weak Label, medRxiv, Cold Spring, NY, USA, 2020.
- [18] A. Abbas, M. M. Abdelsamea, and M. M. Gaber, “Classification of COVID-19 in chest x-ray images using detrac deep convolutional neural network,” *Applied Intelligence*, vol. 51, 2020.]
- [19] L. Li, “Using artificial intelligence to detect COVID-19 and community-acquired pneumonia based on pulmonary CT: evaluation of the diagnostic accuracy,” vol. 296, no. 2, 2020
- [20] A. Rehman, S. Naz, A. Khan, A. Zaib, and I. Razzak, Improving Coronavirus (Covid-19) Diagnosis Using Deep Transfer Learning, MedRxiv, Cold Spring, NY, USA, 2020
- [21] S. Asif, Y. Wenhui, H. Jin, Y. Tao, and S. J. M. Jinhai, Classification of Covid-19 from Chest X-ray Images Using Deep Convolutional Neural Networks, MedRxiv, Cold Spring, NY, USA, 2020.
- [22] Y. Song, Deep Learning Enables Accurate Diagnosis of Novel Coronavirus (COVID-19) with CT Images, MedRxiv, Cold Spring, NY, USA, 2020.
- [23] M. Loey, F. Smarandache, and N. E. Khalifa, “Within the lack of chest COVID-19 X-ray dataset: a novel detection model based on gan and deep transfer learning,” *Symmetry*, vol. 12, no. 4, p. 651, 2020.
- [24] M. Rahimzadeh and A. Attar, “A modified deep convolutional neural network for detecting COVID-19 and pneumonia from chest X-ray images based on the concatenation of Xception and ResNet50V2,” *Informatics in Medicine Unlocked*, vol. 19, 2020.
- [25] A. E. Hassanien, L. N. Mahdy, K. A. Ezzat, H. H. Elmousalami, and H. A. J. M. Ella, Automatic X-ray Covid-19 Lung Image Classification System Based on Multi-Level 5resholding and Support Vector Machine, MedRxiv, Cold Spring, NY, USA, 2020.
- [26] A. M. Alqudah, S. Qazan, H. Alquran, I. A. Qasmieh, and A. Alqudah, “COVID-2019 detection using x-ray images and artificial intelligence hybrid systems,” *Biomedical Signal and Image Analysis and Project*, 2020.
- [27] A. A. Osi, A Classification Approach for Predicting COVID-19 Patient Survival Outcome with Machine Learning Techniques, MedRxiv, Cold Spring, NY, USA, 2020
- [28] S. Kumar, S. Mishra, and S. K. J. M. Singh, Deep Transfer Learning-Based COVID-19 Prediction Using Chest X-Rays, MedRxiv, Cold Spring, NY, USA, 2020.
- [29] I. D. Apostolopoulos, T. A. J. P. Mpesiana, and E. S. i. Medicine, “Covid-19: automatic detection from x-ray images utilizing transfer learning with convolutional neural networks,” vol. 1, 2020.

- [30] M. J. Horry, M. Paul, A. Ulhaq, B. Pradhan, M. Saha, and N. Shukla, X-Ray Image Based COVID-19 Detection Using Pre-trained Deep Learning Models, MedRxiv, Cold Spring, NY, USA, 2020.
- [31] P. K. Sethy and S. K. J. P. Behera, "Detection of coronavirus disease (covid-19) based on deep features," International Journal of Mathematical, Engineering and Management Sciences, vol. 5, 2020.
- [32] Rajaraman, S.; Siegelman, J.; Alderson, P.O.; Folio, L.S.; Folio, L.R.; Antani, S.K. Iteratively Pruned Deep Learning Ensembles for COVID-19 Detection in Chest X-Rays. IEEE Access 2020, 8, 115041–115050.
- [33] Islam, M.M.; Karray, F.; Alhaji, R.; Zeng, J. A Review on Deep Learning Techniques for the Diagnosis of Novel Coronavirus (COVID-19). IEEE Access 2021, 9, 30551–30572
- [34] Chowdhury, M.E.H.; Rahman, T.; Khandakar, A.; Mazhar, R.; Kadir, M.A.; Mahbub, Z.B.; Islam, K.R.; Khan, M.S.; Iqbal, A.; Emadi, N.A.; et al. Can AI Help in Screening Viral and COVID-19 Pneumonia? IEEE Access 2020, 8, 132665–132676.
- [35] Ucar, F.; Korkmaz, D. COVIDiagnosis-Net: Deep Bayes-SqueezeNet based diagnosis of the coronavirus disease 2019 (COVID-19) from X-ray images. Med. Hypotheses 2020, 140, 109761.
- [36] Rahimzadeh, M.; Attar, A. A modified deep convolutional neural network for detecting COVID-19 and pneumonia from chest X-ray images based on the concatenation of Xception and ResNet50V2. Inform. Med. Unlocked 2020, 19, 100360.
- [37] Narin, A.; Kaya, C.; Pamuk, Z. Automatic detection of coronavirus disease (COVID-19) using X-ray images and deep convolutional neural networks. Pattern Anal. Appl. 2021, 24, 1207–1220
- [38] Khobahi, S.; Agarwal, C.; Soltanalian, M. CoroNet: A Deep Network Architecture for Semi-Supervised Task-Based Identification of COVID-19 from Chest X-ray Images. Available online: <https://www.medrxiv.org/content/early/2020/04/17/2020.04.14.20065722> (accessed on 25 May 2021).
- [39] Wang, L.; Lin, Z.Q.; Wong, A. COVID-Net: A tailored deep convolutional neural network design for detection of COVID-19 cases from chest X-ray images. Sci. Rep. 2020, 10, 19549.
- [40] Afshar, P.; Heidarian, S.; Naderkhani, F.; Oikonomou, A.; Plataniotis, K.N.; Mohammadi, A. COVID-CAPS: A capsule networkbased framework for identification of COVID-19 cases from X-ray images. Pattern Recognit. Lett. 2020, 138, 638–643.