Retraction

Retraction: Deep learning methods to analyse and detect the presence of COVID-19 using X-rays (J. Phys.: Conf. Ser. 1916 012170)

Published 23 February 2022

This article (and all articles in the proceedings volume relating to the same conference) has been retracted by IOP Publishing following an extensive investigation in line with the COPE guidelines. This investigation has uncovered evidence of systematic manipulation of the publication process and considerable citation manipulation.

IOP Publishing respectfully requests that readers consider all work within this volume potentially unreliable, as the volume has not been through a credible peer review process.

IOP Publishing regrets that our usual quality checks did not identify these issues before publication, and have since put additional measures in place to try to prevent these issues from reoccurring. IOP Publishing wishes to credit anonymous whistleblowers and the Problematic Paper Screener [1] for bringing some of the above issues to our attention, prompting us to investigate further.

[1] Cabanac G, Labbé C and Magazinov A 2021 arXiv:2107.06751v1
Retraction published: 23 February 2022
Deep learning methods to analyse and detect the presence of COVID-19 using X-rays

P Tamije Selvy1, S K Lalith Sai Kumar1, R Thirumalraj1, G Vimal1
1Department of Computer Science, Sri Krishna College of Technology, Coimbatore, Tamilnadu, India
Email - thirumalrajramakrishnan@gmail.com

Abstract. The COVID-19 was discovered in December 2019 in China's Wuhan. and resulted in a major outbreak in several cities in China and spread globally, continuing to have a devastating influence on the world wide population's health and well-being. The virus affects the respiratory system and it is transmitted through close contact of individuals. Efficient screening of infected patients is a crucial step in standing up to COVID-19. As the virus affects the respiratory system, images of chest X-rays are analyzed using deep learning techniques for early detection of COVID-19. The existing deep learning models identify COVID-19 with an accuracy of 79%. The proposed model focuses on detecting COVID-19 in an effective manner, the model includes the following phases: Preprocessing the image using data augmentation and infusing the trained model with different Convolutional Neural Network architectures. The proposed model uses Residual Neural Network architecture (ResNet-152v2), NASNetLarge, and Visual Geometry Group architecture (VGG16), a Convolutional Neural Network (CNN) which are faster when compared to the already existing systems and have an accuracy of 87.50%, 87.50% and 82% respectively.

1. Introduction
The outbreak of coronavirus threatens to have a disastrous influence on human well being and economies of the world’s community. To reduce the transmission of coronavirus, effective monitoring of affected people is a key step in ensuring that all infected get timely attention and care, as well as to limit the spread of virus. The approach used for identifying coronavirus’ occurrences is Reverse Transcriptase-Polymerase Chain Reaction (RT-PCR) research. It can trace the presence of virus spreading COVID from respiratory specimens gathered from different swabs such as the nose, nasal cavity or middle part of the throat. Though RT-PCR testing is the standard method, it is a very tedious and manual process that is short in supply. Also, the responsiveness of the RT-PCR test is generally low and has not been documented clearly and accurately to date.

An additional screening technique used for the detection is radiography analysis, in which chest X-ray images are analyzed to check for traces associated with the virus. It is used for the purpose of screening COVID-19 outbreaks, and most positive COVID-19 cases documented irregularity in the X-Ray images in their research. The use of X-Rays for COVID-19 identification has many advantages, particularly in highly affected regions:

- CXR imaging allows for quick treatment of persons who are suspected to have the traces of virus.
- This is conducted in conjunction with viral testing, especially in containment zones where they run out of capacity, or also as a separate option where virus detection is not an option.
● In many medical centers and scanning facilities, Chest X-ray imaging is broadly used and cost-effective and it is also considered common equipment in most hospitals. In fact, due to high equipment and maintenance costs, CXR scanning is more readily available than Computed tomography.

● The presence of the portable CXR system ensures that scanning can be carried out in a separate room, thereby greatly deterring the transmission of coronavirus.

● CXR scanning is also recommended being helpful in cases in which persons with original negative RT-PCR test findings report to the intensive care unit with increasing signs.

Driven by the urgent need to build methods to tackle the COVID-19 disease outbreak, inspired by the scientific community’s open source and freely accessible initiatives this study introduces the Deep convolutional neural network architectures such as RESNET15, NASNetLarge and VGG16 which are adapted to identify COVID-19 cases from open source and publicly accessible CXR images, shown in Figure 1.

![Sample X-Rays for Covid-19 and Normal](image)

**Figure 1.** Sample X-Rays for Covid-19 and Normal

2. Related Works

Chest radiography examination has been an indicative tool widely used in medical care. During the last few years it has been used to differentiate and monitor the progression of a few respiratory problems, such as Crohn’s disease, cellular breakdown in the lungs or pneumonia and to evaluate abnormalities in the cardiothoracic region [1]. Therefore, the study of CXR images of the suspected individuals provides an enormous possibility for screening steps which help in the early detection of coronavirus [2]. Noticeably more, it is understood that, despite their feasibility, Polymerase Chain Reaction (PCR) [3] considers that there is a degree of false negative, so the radiological examination is yet another instrument to assist and validate the study of these patients.

The studies conducted recently show that there is distinguishing evidence associated with COVID-19, it could be identified with other respiratory illnesses with comparative attributes such as pneumonia [4]. A fully programmed system for the examination of chest X-Ray images, identifying obvious cases of COVID-19, will minimize the great work and risks of the healthcare professionals allowing a strong and replicable analysis to support the clinical complex chain.

To differentiate instances of COVID-19 from pneumonia a 3-step methodology was built to improve the ResNet-50 which is a pre-trained architecture to boost model efficiency and decrease the training time. This is a useful model in the advance screening of COVID-19 reports and helps lower the amount of distress. By developing freely accessible source code and datasets, this model introduces an appropriate Convolutional Neural Network model. It offers an algorithmically advanced and relatively reliable method for the multi-class classification of three main classes of illness along with healthy people [5]. It yields the accuracy of 96.23% in 41 iterations.

This deep learning technique for transfer learning uses random oversampling and weighted class loss function methods. To perform chest X-Ray image multi-class classification ResNet, Inception-v3 and NASNetLarge were used. In comparison to other models, NASNetLarge showed better performance, which is again related to other newly proposed architectures. Using standard performance measures like precision, accuracy, recall, area under the curve, specificity, and F1 score, each trained method was assessed. In the binary classification of COVID-19 samples, NASNetLarge proved to be
more effective in particular [6]. To produce better outcomes, more profound learning models and preprocessing strategies can also be considered.

The studies conducted on examination of chest X-Ray images use one of the transfer learning strategies known as fine-tuning. For fine tuning the CXR images, the ImageNet's pretrained weight is used to deal with the VGG-16 model, it is also known as Attention-based VGG-16. The primary components of this model are the Attention Module, the Convolution Module, the FC layer, and the Softmax Classifier [7]. The approach relies on the pre-trained Deep Learning model VGG-16. It collects low-level functions using its small-sized kernel, which is suitable for Chest X-Ray images with a smaller number of layers compared to its equivalent VGG-19 model is the reason to prefer VGG-16.

3. Methodology
The proposed model focuses on the preprocessing and data augmentation and uses pretrained models i.e, ResNet152V2, NasNetLarge and VGG16 for classifying dataset in two classes COVID X-rays and Normal X-Rays.

The system classifies the input images into categories. It marks the X-ray as COVID-19 positive or negative. First, the COVID Chest X-ray dataset is preprocessed and used in this analysis. Then the role of the classification model is described, which is based on the principle of Deep CNN approaches. Finally, the input images are classified.

3.1. Flow Diagram
The Flow Diagram of the proposed model is shown in Figure 2.

![Flow Diagram of Proposed model.](image)

3.2. Dataset Description
- Name: covid-chestxray-dataset [8]
- Source: GitHub
- Description: Chest X-rays of infected people that are COVID-19 positive or suspected to have the infection are gathered and those datasets are available to the public.
Metadata: Sex, Age, Survival Status, Date of Scan, Findings and so on are the informations given about the data. The Figure 1 shows the sample images contained in the dataset.

3.3. Pre-Processing and Data Augmentation
In order to minimize the issue of model overfitting, a data augmentation approach is applied. There is a high chance of overfitting because of the in-depth design of the pre-trained system if the amount of data set is minimal. Additional images were created utilising data augmentation in order to avoid this limitation. Utilizing three phases, resizing, flipping and rotation, augmentation was implemented. A dimension of 224 x 224 x 3 was used for the resizing. The applied augmentation strategies attempted to improve the generalisation of the developed framework. Only on the X-ray training collection of data the data augmentations are introduced.

3.4. ResNet152V2
The Residual Network (ResNet) is a CNN architecture shown in Figure 3 has hundreds or thousands of convolutional layers. ResNet includes a wide range of levels with powerful output. Classification, feature extraction, and prediction are the few applications of it. Residual networks with a depth of up to 152 layers are evaluated on the ImageNet [9] and it is deeper than VGG networks, but much less complicated. Before each weighted layer, Version2 utilizes batch normalization, it is the main distinction among ResNet 152V2 and the initial version. ResNet has a high success rate in the area of image detection tasks. It is also efficient in the localization task.

3.5. NasNetLarge
NASNet-Large a CNN, trained on large number images from ImageNet datasets. The system will categorize pictures into thousand types of things, like as a monitor, mouse, pen, and several other objects. As an effect, for a large dataset, it has studied rich function representations. It has a picture input scale of 331-by-331 for image inputs [10]. The architecture diagram of NasNetLarge is shown in Figure 4.
The Very Deep Convolutional Network (VGG) was initially demonstrated by K. Simonyan and A. Zisserman in 2014 in the article "Very Deep Convolutional Networks for Large-Scale Image Recognition". On ImageNet, which is a data source including over 14 million pictures associated with various classes, VGG attains 92.7%, a top accuracy rate in it [11]. The analysts analyzed the influence of depth on precision. They use a simple convolutional neural network with quite limited (3x3) convolution filters with phase and pad 1, 2x2 max-pooling with phase 2, for this reason, and increase the depth to 16–19 layers, which at that time was appropriate [12]. The generalization of the model is improved by the spike in the number of levels. The number of levels seems to be the only distinction among VGG16 and VGG19. The convolutional neural network, however, is utilized to evaluate the picture object [13]. The architecture diagram of VGG16 is shown in Figure 5.

Figure 5. Architecture Diagram of VGG16.

4. Result and Analysis

4.1. Model Evaluation
The basic parameters of evaluation such as precision, sensitivity, specificity, accuracy, False Negative Rate, F1 score, False Positive Rate and so on were used to test the feasibility of this approach. Accuracy indicates how correctly the total number of covid X-rays from the dataset are classified. The proposed
model's sensitivity or true positive levels. It is the ratio between the number of X-rays that are expected to be COVID-19 and the number of X-rays in the collected data. The specificity is the ratio between the number of X-rays that are expected to be regular to all normal X-rays in the data set. Precision shows whether the X-ray is projected as infected and how it is reflected by the real existence of infection. The lower the false positives and false negatives value, the higher the efficacy of the proposed system. The following equation 1-6 formulas were used to find the evaluation parameters.

\[
\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \\
\text{Precision} = \frac{TP}{TP + FP} \\
\text{Recall} = \frac{TP}{TP + FN} \\
\text{Specificity} = \frac{TN}{TN + FP} \\
\text{Sensitivity} = \frac{TP}{TP + FN} \\
\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}
\]

Where TP denotes the total number of correctly detected COVID instances, FP denotes the total number of falsely detected COVID instances, and FN denotes the total number of falsely detected normal cases, TN denotes the total number of correctly detected normal cases. The numerical values of these parameters are shown in Figure 6.

4.2. Experimental Results

ResNet152V2, NasNetLarge, and VGG16 were three trained CNN models used for the experiment. Figure 7, Figure 8, and Figure 9 represent the training loss and accuracy of the ResNet152V2, NasNetLarge, and VGG16 models respectively with the number of epochs. Each model uses 25 epochs. The training accuracy and the value accuracy of the VGG16 model shown in Figure 9 is less accurate in comparison with the other two models. However, it produces minimum training loss and value loss. Comparing the graphs of each model, it is found that the NasNetLarge model has more training accuracy and value accuracy compared to the other models. On analyzing the graphs of NasNetLarge and ResNet152V2, it is found that the training accuracies and value accuracies are very similar.

A total of three models have been developed in the study, and the efficiency of each system has been assessed with respect to the behaviour described in the above chapters. The results obtained show that NasNetLarge performs better than the other two models with the best degree of precision of 87.50%. Both ResNet152V2 and NasNetLarge produced similar results, and the sensitivity of NasNetLarge is higher than ResNet152V2. The key motive for using X-ray scans for earlier COVID-19 detection was to reduce the sensitivity issue of the RT-PCR and also the false positive rate of Lab experiments of RT-PCR is found to be lower sensitivity of the regular method used for detection is the main obstacle faced in managing the pandemic. Whereas higher sensitivity indicates that there are only a few X-rays left undetected with COVID-19, which eventually decreased the distribution of COVID-19. ResNet152V2 achieved 66.67% sensitivity whereas NasNetLarge achieved highest sensitivity of 99.85% other parameter performances are visually represented in Figure 10.
Figure 6. Confusion matrices of proposed models.

Figure 7. Accuracy and loss of training and testing data for ResNet152V2.

Figure 8. Accuracy and loss of training and testing data for NasNetLarge.
Figure 9. Accuracy and loss of training and testing data for VGG16.

Table 1. Parameters and Performance Metrics of the Models

| Measures    | ResNet152V2 | NasNetLarge | VGG16 |
|-------------|-------------|-------------|-------|
| Accuracy    | 87.50%      | 87.50%      | 75%   |
| Sensitivity | 75%         | 99.58%      | 99.58%|
| Specificity | 99.28%      | 83%         | 60%   |
| Precision   | 99.38%      | 66.67%      | 60%   |
| Recall      | 75%         | 99.38%      | 99.38%|

Figure 10. Pictorial representations of performance analysis.
5. Conclusion
This study proposes models such as ResNet152V2, NasNetLarge and VGG16 for the earlier identification of coronavirus traces from the chest X-ray scans and these models are trained with nearly hundreds of preprocessed images and trained with them. Using standard performance measures, like accuracy, precision, recall, specificity, and F1 score, each trained model was analyzed. In spite of having X-ray scans in limited amounts, all the three variations of the proposed models obtained impressive results on the test dataset which is shown in Table 1. The best accuracy of the study is 87.5% and the significant sensitivity percentage of 99.58%. The proposed model will definitely play a significant role in early and rapid identification of COVID-19 with such a higher precision, thereby reducing testing time and expense. According to the study done, models have been shown to obtain different scores in various situations but NASNetLarge exhibited better results, particularly in binary classification COVID-19 X-ray scans. In order to produce improved outcomes, more approaches using deep learning can be investigated as an extension of this work.

References
[1] Guan, W. J., Ni, Z. Y., Hu, Y., Liang, W. H., Ou, C. Q., He, J. X. & Zhong, N. S. (2020). Clinical characteristics of coronavirus disease 2019 in China. New England journal of medicine, 382(18), 1708-1720.
[2] Jacobi, A., Chung, M., Bernheim, A., & Eber, C. (2020). Portable chest X-ray in coronavirus disease-19 (COVID-19): A pictorial review. Clinical imaging.
[3] Wu, G., & Li, X. (2020). Mobile X-rays are highly valuable for critically ill COVID patients. European radiology, 30, 5217-5219.
[4] Mao, B., Liu, Y., Chai, Y. H., Jin, X. Y., Lu, H. W., Yang, J. W., ... & Xu, J. F. (2020). Assessing risk factors for SARS-CoV-2 infection in patients presenting with symptoms in Shanghai, China: a multicentre, observational cohort study. The Lancet Digital Health, 2(6), e323-e330.
[5] H. Anandakumar and K. Umamaheswari. A bio-inspired swarm intelligence technique for social aware cognitive radio handovers, Computers & Electrical Engineering, vol. 71, pp. 925–937, Oct. 2018. doi:10.1016/j.compeleceng.2017.09.016
[6] R. Arulmurugan and H. Anandakumar, Early Detection of Lung Cancer Using Wavelet Feature Descriptor and Feed Forward Back Propagation Neural Networks Classifier, Lecture Notes in Computational Vision and Biomechanics, pp. 103–110, 2018. doi:10.1007/978-3-319-71767-8_9
[7] Sitaula, C., & Hossain, M. B. (2020). Attention-based VGG-16 model for COVID-19 chest X-ray image classification. Applied Intelligence, 1-14.
[8] Covid Chest X-Ray Dataset Link : https://github.com/ieee8023/covid-chestxray-dataset.
[9] Elshennawy, N. M., & Ibrahim, D. M. (2020). Deep-Pneumonia Framework Using Deep Learning Models Based on Chest X-Ray Images. Diagnostics, 10(9), 649.
[10] Khan, I. U., & Aslam, N. (2020). A deep-learning-based framework for automated diagnosis of COVID-19 using X-ray images. Information, 11(9), 419.
[11] Yadav, S., Sandhu, J. K., Pathak, Y., & JadHAV, S. (2020). Chest X-ray scanning based detection of COVID-19 using deep convolutional neural networks..
[12] Simonyan, K., & Zisserman, A. (2014). Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556.
[13] Hossin, M., & Sulaiman, M. N. (2015). A review on evaluation metrics for data classification evaluations. International Journal of Data Mining & Knowledge Management Process, 5(2), 1.