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Classification of COVID-19 Cases: The Customized Deep Convolutional Neural Network and Transfer Learning Approach

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Abstract

The recent advancements under the umbrella of artificial intelligence (AI) open opportunities to tackle complex problems related to image analysis. Recently, the proliferation of COVID-19 brought multiple challenges to medical practitioners, such as precise analysis and classification of COVID-19 cases. Deep learning (DL) and transfer learning (TL) techniques appear to be attractive solutions. To provide the precise classification of COVID-19 cases, this article presents a customized Deep Convolutional Neural Network (DCNN) and pre-trained TL model approach. Our pipeline accommodated several popular pre-trained TL models, namely DenseNet121, ResNet50, InceptionV3, EfficientNetB0, and VGG16, to classify COVID-19 positive and negative cases. We evaluated and compared the performance of these models with a wide range of measures, including accuracy, precision, recall, and F1 score for classifying COVID-19 cases based on chest X-rays. The results demonstrate that our customized DCNN model performed well with randomly assigned weights, achieving 98.5% recall and 97.0% accuracy.

Keywords

Covid19, transfer learning, deep convolutional neural network, medical imaging.

Introduction

The 2019 Coronavirus (COVID-19) pandemic has shaken the world and disrupted our daily lives. The COVID-19 outbreak has exposed healthcare and essential services to a massive challenge in combating the virus and induced unprecedented pressure (Vyas et al. 2021). According to the Johns Hopkins Coronavirus Resource Center, by the end of January 2022, more than 365 million people possibly contracted COVID-19, and more than 5.6 million people have died from COVID-19 ("Johns Hopkins" 2021). Noticeably, the United States has suffered more than 800,000 deaths among nearly 74 million cases ("Johns Hopkins" 2021). Timely diagnosis and treatment are essential to combat and control the spread of the Coronavirus (Reuter-Oppermann et al. 2020; Tao et al. 2020; Tsoi et al. 2021). The reverse transcription-quantitative polymerase chain reaction (RT-qPCR) is the standardized testing method to identify if a person is infected. Recent studies, such as (Tao et al. 2020), indicate that the RT-qPCR testing method is time-consuming and can lead to false positives. Imaging techniques, such as the Computed Tomography (CT)-scan, can be used to support the diagnosis of COVID-19. However, these imaging techniques still require the manual involvement of healthcare experts. Deep Transfer Learning (TL) techniques can facilitate fast, reliable, and efficient automated methods for detecting COVID-19 from image data.

Deep learning(DL) is a branch of artificial intelligence that works on the functionality of human brain and neurons for learning purposes. The word "deep" signifies the number of hidden layers that are many in comparison to simple neural networks (i.e., with single hidden layer). A Deep Convolutional Neural

Network (DCNN) is a deep learning-based neural network that comprises various hidden neural network layers, including convolutional and pooling layers. DCNNs are mainly used for image classification. Implementing a DCNN from scratch has advantages such as learning complex representations at different levels of abstraction in images and achieving human-level performance (Khan et al. 2020). In DCNN, the utilized convolutional layers extract the imagery features automatically due to striding filters or kernels rather than performing a feature extraction manually (Yin et al. 2020).

Recently, DCNN has emerged as a popular choice for various medical imaging problems, such as malignant tumor detection, colon cancer classification, and glaucoma diagnosis. Problem-specific customized DCNN architectures and pre-trained TL models can show promising performance for these diagnostic tasks. TL has emerged as an alternative way of training deep neural networks wherein a neural network is trained upon the results generated by already trained models. In medical image classification tasks, these pre-trained models utilize existing ImageNet data that consists of Millions of images from numerous domains (Horry et al. 2020). Furthermore, a model trained on one task is re-purposed for a second related task in TL techniques. This re-purposing is a popular approach in deep learning, where pre-trained models are used as the starting point for classification tasks. TL enables rapid progress and improved performance when modeling the second task. Thus, this work's overarching goal is to utilize the aforementioned advantages of DCNN to build a customized pipeline for automatizing the classification of COVID-19 cases to help physicians by suggesting an alternative opinion while diagnosing the patient's chest x-rays. We have also compared the classification performance of our customized DCNN with famous TL models.

We presented the implementation of our customized DCNN from scratch and also presented the utilization of various TL models such as ResNet50 (He et al. 2016), VGG16 (Simonyan and Zisserman 2015), DenseNet121 (Huang et al. 2017), InceptionV3 (Szegedy et al. 2016), and EfficientNetB0 (Tan and Le 2019). We demonstrate how neural network-based DCNN and TL techniques can be used to classify COVID-19 cases. The overarching contribution of this paper is to introduce and evaluate a precise classification approach that automates the early detection of COVID-19 cases. More specifically, the contributions of this paper are summarized as - First, we proposed a customized DCNN and TL COVID-19 classification pipeline. The whole approach takes less computational power because customized DCNN possesses a simple architecture. Our modeling pipeline can extract the features by randomly assigned weights from scratch and by utilizing pre-trained ImageNet weights as well. Second, our approach can classify the Normal vs. COVID-19 positive cases based on chest X-ray images. Our preprocessing module scales all COVID-19 and non-COVID-19 case images to reduce the image quality imbalances and noises, thereby training the models to focus on lung features through image augmentation. Third, the proposed approach may rectify future challenges, such as the emergence of new COVID-19 variants, and further training of presented models on new variant datasets would also strengthen the classification efficiency. Moreover, the TL learning-based automated diagnosis can improve the medical decision-making process by potentially eliminating the routine process of obtaining a second opinion. Specifically, the DCNN and TL analysis of high-quality medical images can be an alternative to the second opinion for the diagnosis of COVD-19.

In this paper, we described DCNN, TL, and COVID-19 detection by complementing prior research works such as (Ahuja et al. 2021; gifani et al. 2021; Jaiswal et al. 2020; Li et al. 2021; Pathak et al. 2020; Perumal et al. 2021; Shamsi et al. 2021; Singh et al. 2020). We then describe our DCNN and TL pipeline in detail, which helps understand how deep neural network techniques can help classify COVID-19 cases faster. Further, we highlight the evaluation matrix parameters to assess the performance of our approach. We discuss the obtained results with different TL pre-trained models and discuss their performances. Finally, we highlight some potential enhancements for this work in the conclusion section.

Relevant studies

During the current COVID-19 pandemic, the integration of AI solutions in healthcare has made it possible to detect COVID-19 at early stages (Mei et al. 2020), and the Mount Sinai Health System in New York City has taken the initiative ("Mount Sinai" 2020). To foster the efforts of medical staff and physicians, recent studies have explored the utilization of supervised AI techniques to detect COVID-19 pneumonia-based lung diseases with improved diagnostic efficiency (Ozturk et al. 2020). For example, Jin et al. (2021) have implemented a hybrid model that comprises three distinct steps to diagnose the COIVD-19. The steps incorporate three essential image-based operations, i.e., features extraction, feature selection, and training support vector machine (SVM) classifier. However, according to Laino et al., (2021), such AI-based techniques should be adequately trained to distinguish between COIVD-19 and normal chest images to attain highly potent diagnostic results. Moreover, chest X-ray images usually contain a distinct view of the postero-anterior and latero-lateral of the chest. Hence these views should be considered during the training of models, along with the patient's features such as age and health conditions (Laino et al. 2021).

Moreover, deep learning-based TL as a branch of AI has emerged as an essential methodology for medical imaging and helping in fighting with COVID-19 by assessing X-rays and CT scan Images (Jiang et al. 2021; Meng et al. 2020; Wu et al. 2020). For example, Yang et al., (2020) have utilized the DenseNet (an enhanced version of deep convolutional neural network) based TL model on high-resolution computed tomography (HRCT) test results to diagnose the COVID-19 disease at the very beginning of its appearance in China. Further, it has been observed that the utilization of such deep learning-based models can detect the COVID-19 within seconds and can beat the human diagnostic time from 5 - 10 minutes to 30 sec (Yang et al. 2020). Thus, DL and TL techniques can save diagnostic time and fasten the process during crises. Some studies, such as (Horry et al. 2020; Jaiswal et al. 2020; Loey et al. 2020; Singh et al. 2020), adopted TL techniques to detect COVID-19 positive cases through available medical image datasets. According to (Horry et al. 2020), using a chest X-ray dataset instead of a CT scan is beneficial and requires less processing due to low ionizing radiations.

Existing studies such as (Jiang et al. 2021; Tabik et al. 2020) have encountered the problem of the unavailability of adequate datasets for the training of deep learning and TL-based models. Hence, the authors in (Jiang et al. 2021) utilized conditional generative adversarial net (cGAN) to generate COVID-19 CT images data from the sample datasets to rectify the problem of data unavailability. In (Tabik et al. 2020), the authors created the homogeneous and balanced dataset COVIDGR-1.0 that comprises 426 positive and 426 negative PA (PosteroAnterior) Chest X-rays views. Distant Domain Transfer Learning (DDTL) is a TL-based model that has been adopted by (Niu et al. 2021) along with a reduced-size unit to detect the COVID-19 from CT images. In (d. S. Gomes and d. O. Serra 2021), the authors proposed a new machine-learning-based computational tool by utilizing fuzzy systems to analyze the propagation of COVID-19 dynamically.

We have observed that existing studies, e.g., (Ahuja et al. 2021; gifani et al. 2021; Jaiswal et al. 2020; Li et al. 2021; Pathak et al. 2020; Perumal et al. 2021; Shamsi et al. 2021; Singh et al. 2020), have utilized CT scan images for the detection of COVID-19. However, CT scans are costly and only performed in special circumstances (Horry et al. 2020). In contrast, X-rays are a cost-effective alternative for mass COVID-19 detection. Studies, such as (Chowdhury et al. 2020; Horry et al. 2020), have considered an amalgamation of COVID-19 and viral pneumonia images, which may create uncertainty while detecting COVID-19 cases. Models trained on pneumonia images may inaccurately predict the outcome (Jaiswal et al. 2020). While COVID-19 and pneumonia chest X-ray images share some common properties, there are variations over time, e.g., COVID-19 chest X-ray testing results vary from the first day to the seventh day of testing (Mazurowski et al. 2019). Therefore, relying on pneumonia chest X-ray image datasets is not advisable for COVID-19 studies. Hence, we have utilized COVID-19 chest X-ray images from (Cohen, Morrison, and Dao 2020; Cohen, Morrison, Dao, et al. 2020). Most relevant studies such as (Ahuja et al. 2021; gifani et al. 2021; Li et al. 2021; Perumal et al. 2021; Shamsi et al. 2021), have relied on the various TL models, whereas we have built the proposed DCNN from scratch to train the model by using random weights and by providing COVID-19 X-ray images rather than relying on fixed ImageNet weights that primarily used in case of TL model training. However, we also trained the TL models and compared them with our DCNN to check the performance efficiency.

Customized DCNN and transfer learning pipeline

Figure 1 shows the entire pipeline, including data collection, data preprocessing, customized DCNN architecture, and utilized TL architectures and resultant classification of COVID-19 cases. These phases are explained in the following subsections.

Data Pre-processing

An extensive data preprocessing is required for the image classification tasks. Therefore, having a variety of image sizes in the datasets, to ensure a similar aspect ratio, we have resized all images to 224 × 224 pixels for performing efficient classification. Image augmentation is essential for training models (Zhang et al.

2019). Therefore, we augmented the images by the left and right rotation and zoomed in and out with a range of 80% -120% to train the model to recognize any distorted images.

Customized DCNN

DCNN is a combination of the input layer, hidden layer, and output layer. It is generally utilized for image classification by assigning different weights to the various aspects of the image to differentiate all image components. Instead of relying on conventional matrix multiplication, it uses the convolutional mathematical operation that integrates the product of two distinct functions. Such convoluted results are passed between the DCNN layers. As shown in Figure 1, We have used three convolutional blocks that are a group of connected layers to extract the image features, such as color components, length, area, circularity, gradient magnitude, gradient direction, grayscale intensity, edges for training purposes. Each convolutional block comprises Conv-2D layers, max-pooling layer, dropout, and batch normalization layer. The max-pooling layer calculates the largest values for image feature maps. Batch normalization is used to standardize image inputs to the layer and further improves learning by lowering the number of epochs. The dropout layer reduces the DCNN over-fitting by reducing the number of parameters during the training process. We have used a flatten layer to convert the pooled feature map into a single order vector array that further passes into attached dense layers responsible for generating binary classification results.

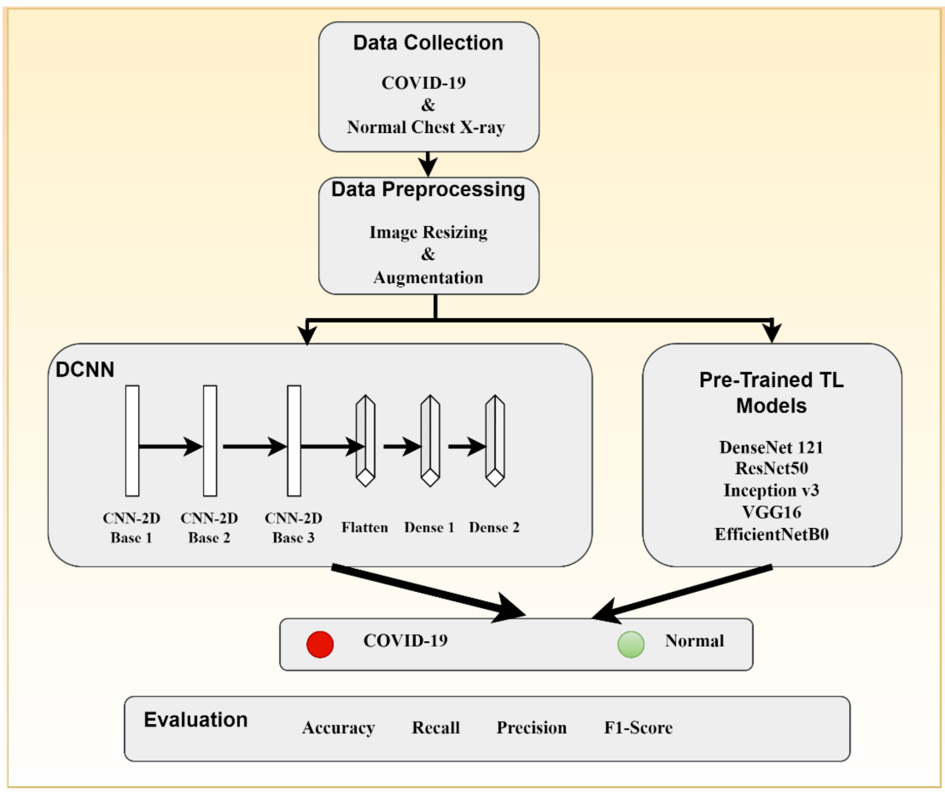


Figure 1. Customized DCNN and Transfer Learning (TL) pipeline.

TL Architectures

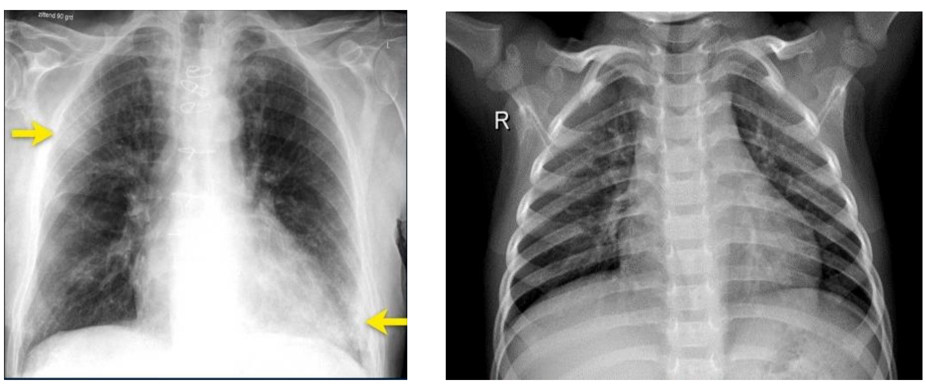
We have utilized convolutional neural network (CNN) based pre-trained model architectures, such as ResNet50 (He et al. 2016), VGG16 (Simonyan and Zisserman 2015), DenseNet121 (Huang et al. 2017), InceptionV3 (Szegedy et al. 2016), and EfficientNetB0 (Tan and Le 2019). These models are deep neural networks comprising various interconnected layers. DenseNet121 is a deep neural architecture connecting layers in a feed-forward fashion to resolve the vanishing gradient problem. The suffix 121 represents the combination of different convolution, classification, pooling, transition, and dense blocks. Residual Network with 50 layers (ResNet50) is a classic neural network architecture that has been extensively studied for various image classification tasks and has won the 2015 ImageNet challenge. VGG16 is a 16-layer deep architecture named after its inventor, the Visual Geometry Group of Oxford University. VGG16 has been trained on millions of images. Therefore, it is widely used in research for image classification tasks. InceptionV3 is 48 layers deep pre-trained model developed by the Inception team of Google. It is developed as a wider and deeper model to perform better but restrain the computational cost. These models are available in the Keras library (available at. https://keras.io/api/applications/).

Furthermore, the VGG16 network uses a smaller convolution kernel and piece-wise convolution to extract the detailed local feature information. In the InceptionV3 network, the mixed modules decompose two-dimensional convolution into two one-dimensional convolutions, which increases the nonlinearity and the width of the network to eliminate the representation bottleneck. The ResNet50 network has a deeper network structure and the residual module, which may solve the degradation problem in the optimization process and enhance learning ability. The DenseNet121 network reinforces feature propagation, encourages feature reuse, and substantially cuts down the number of parameters [22]. The EfficientNet is another CNN-based TL architecture that uses compound coefficient for scaling the depth, width, and resolution dimensions. The EfficientNet has variants ranging from B0 to B7. B0 is a base model on which the rest of the versions have developed. All variants are trained on the ImageNet dataset.

Evaluation

Datasets

We have used the COVID-19 X-Ray image data set for positive cases [26], [27], and normal chest X-Ray images for negative cases [34]. The data comprises 450 images of positive COVID-19 cases and 450 images of normal cases. Further, we split the COVID-19 and normal image data into the ratio of 85% and 15% for training and testing purposes of TL models, respectively. Figure 2a shows the sample image of COVID-19 positive patient's chest X-ray, whereby yellow arrows indicate the increased pulmonary infiltration areas. Figure 2b shows the chest X-ray image of a healthy human being.



a) b)

Figure 2. a) COVID-19 positive case chest X-ray (increased pulmonary infiltration shown by yellow arrows). b) Normal patient (non-COVID-19) chest X-ray.

Experimental setup and performance metrics

We have utilized the metrics of recall, precision, F1 score, and accuracy for performance evaluation. These evaluation parameters are critical to check how precisely models predict correct cases (i.e., positive cases as the positive and negative cases as negative) and how efficiently these predictions were made (i.e., rate of the correct prediction in terms of high TL model accuracy). TP, TN, FP, and FN represent the number of true positive, true negative, false positive, and false negative COVID-19 cases, respectively. The recall represents the correctly classified positive classes, precision represents the percentage of classified positive classes among all classified examples, F1 refers to the mean of precision and recall. Accuracy refers to the overall rate of correct predictions.

The formulas are (Powers 2011):

Precision = TP / TP+FP (1)

Recall = TP / TP+FN (2)

F1 score = 2(precision x recall)/precision + recall (3)

Accuracy = (TP+TN) / (TP+FP+FN+TN) (4)

Our experimental setup utilized the Google Cloud Platform (GCP) deep learning VM with a Tesla K80 GPU with 2496 CUDA core and 13GB GDDR5 vRAM. We trained the DCNN and all the utilized TL models for ten epochs with mini-batch sizes of 32 image instances. We considered the small learning rates for the subsequent epochs.

Result and discussion

In the customized DCNN, we have used the Rectified Linear Unit (ReLU) activation function among all convolutional blocks, which helps spare the model from the vanishing gradient descent problem. We increased the number of filters from convolutional blocks 1 to 3 for image feature extractions. We have used the sigmoid activation function at the last dense layer to output the binary labels.

Models	**Accuracy**		**Recall**		**Precision**		**F1 Score**	
	Random Wt.	Fixed FE	Random Wt.	Fixed FE	Random Wt.	Fixed FE	Random Wt.	Fixed FE
DCNN	97.01	-	98.46	-	98.51	-	97.06	-
EfficientNetB0	91.04	91.79	89.86	91.18	89.55	91.04	90.91	91.73
DenseNet121	96.55	96.55	95	96.55	98.28	96.55	96.61	96.55
ResNet50	96.55	50	98.21	50	94.83	58	96.49	54
InceptionV3	80.17	96.55	78.68	95	82.76	98.28	80.67	96.61
VGG16	93.10	96.55	93.10	98.21	93.10	94.83	93.10	96.49

Table 1. Comparison of DCNN with pre-trained TL models for various evaluation measures.

Table 1 describes the performance of different models on the test dataset with pre-trained (i.e., fixed feature) and without pre-trained weights (i.e., random) except the DCNN because it used randomized weights only. Professionals utilized the ImageNet weights to train the pre-trained models in standard practice. We utilized both randomly generated weights and ImageNet weights to train the models for getting optimum results. Such evaluation parameters are essential to check how precisely models predict correct cases (i.e., positive cases as positive and negative cases as negative) and how efficiently these predictions were made (i.e., rate of correct prediction in terms of high TL model accuracy). As Table 1 shows, our DCNN has achieved 97.01% accuracy on random weights along with 98.46% recall, 98.51% precision, and 97.06% F1 score. Hence, outperformed the other models while using random weights. The DenseNet121 model gets the same 96.55% accuracy on the test set with both ImageNet and randomly assigned weights. ResNet50 performed better on random weights with 96.55% accuracy than ImageNet weights with 50% accuracy, which is not even comparable. InceptionV3 obtained 96.55% accuracy with ImageNet weights compared to random weights with 80.17% accuracy. VGG16 got 96.55% accuracy with ImageNet weights compared to random weights with 93.10% accuracy. EfficientNetB0 has achieved 91.04% accuracy at random weights and 91.79% at ImageNet weights.

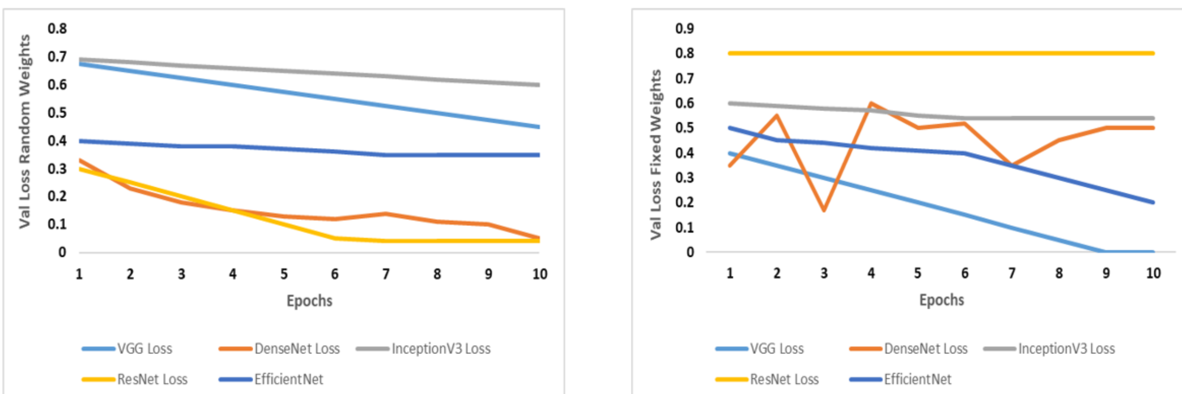
Existing Studies	(Singh et al. 2020)	(Pathak et al. 2020)	(Jaiswal et al. 2020)	(Li et al. 2021)	(Perumal et al. 2021)	Our DCNN	(Nasser et al. 2021)
Accuracy %	95.70	93.01	97.48	87.00	93.00	**97.01**	98.60

Table 2. Comparison of proposed DCNN with existing studies.

As shown in Table 2, we have compared our DCNN test accuracy with existing approaches in the literature. Our customized DCNN has performed comparatively well. Furthermore, based on the results, in TL models, we can assert that DenseNet121 and VGG16 models performed well on utilized small datasets, whereas InceptionV3 and ResNet50 required more data for better training. These models were pre-trained on general images unrelated to COVID-19, which likely led to the variations in the observed results.

The TL model's overarching goal is to get high training and validation accuracy and low training and validation loss. Validation accuracy and loss are calculated on training data that is called validation data to judge the model's over-fitting and under-fitting states. Loss functions, such as binary cross-entropy and categorical cross-entropy, measure how well the models are trained on the given dataset. Thereby, these tend to drive the variations in loss values. Utilization of optimizers, such as Stochastic gradient descent and Adam, tend to optimize the performance of TL models by reducing the loss values. However, iterative testing is required before identifying the best fit optimizer for TL models.

Furthermore, as shown in Figure 3a and 3b, when we analyzed the TL model's validation losses, in DenseNet121, the model's losses decreased when using random weights and minorly varied when using fixed weights. In InceptionV3, there was a steady decrease in loss when using random weights, whereas the model's loss decreased unsteadily using fixed weights. ResNet50's loss decreased at random weights, whereas the loss remained constant after initial epochs at fixed weights. EfficientNetB0's validation loss values decreased at fixed weights more than using random weights. Overall, all models achieved the goal of decrements in losses. However, it requires additional parameter tuning to normalize all results.



a) **b)**

Figure 3. a) Validation losses per epochs at random weights; b) Validation losses per epochs at fixed weights.

Conclusion and future work

In this article, we proposed a customized DCNN and implemented different TL techniques used for medical image classification. The obtained results show that among all trained models (i.e., DCNN and pre-trained), DCNN classified the COVID-19 cases with 97.01% accuracy on random weights. Note that data privacy is a big concern. The practitioners may utilize the Secure Shell Authentication Protocol (SSH) during the data transfer process to the cloud servers. They can download the GCP software development kit to use local machine resources such as Jupyter Notebook while using the computational power of GCP.

Future research directions could consider the improvement of the algorithms to get more precise results. Further, a large dataset will be required that consists of X-ray Images of different COVID-19 strains such as the Middle East respiratory syndrome (MERS), severe acute respiratory syndrome (SARS), and COVID-19 for enhancing the detection of the disease in the early stages. Besides, lung nodules detection and lung segmentation can be performed in preprocessing steps for X-ray images.

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