Effect of image enhancements in classification of Chest X Ray(CXR) for diagnosis of COVID 19

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Abstract

The COVID-19 pandemic since March 2020 has been causing a major outbreak,having a severe impact on the health and life of many people globally. One of the crucial step in fighting COVID-19 is the ability to detect the infected patients early enough, and put them under special care. One method that is attracting much interest from both the clinical and the AI community is using Chest X-ray (CXR) imaging for early screening of COVID-19 patients . Inspired by earlier works, we study the application of deep learning models to detect COVID-19 patients from their chest radiography images.In particular, this paper investigates into the effect of different image enhancements techniques, both in spatial and fourier/frequency domain on the classification model. Transfer learning on a subset of the generated dataset was used to train two popular architectures: VGG16 and ResNet50 networks to classify images. After evaluating models with the test dataset,on average sensitivity rate was 90% and specificity rate of around 95% was achieved for best image enhancement scenarios, which was Histogram Equalization with low pass filtering in frequency domain. High sensitivity and specificity is encouraging, as it shows the promise of using X-ray images for COVID-19 diagnostics. The paper also shows that the combinations of the two domains methodologies will result in a noise free sharp image with a very good contrast, which increase the positive evaluation metrics by nearly 3% .

1 Introduction

The Coronavirus Disease 2019 (COVID-19),caused by the infection of individuals by the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) continues to have a devastating effect on the health and well-being of the global population. As of 24th November 2020, there are have been nearly 60M Patients with COVID19 were recorded, and over 1.4M have lost their lives.

A critical step in the fight against COVID-19 is effective screening of infected patients, such that those infected can receive immediate treatment and care, as well as be isolated to mitigate the spread of the virus. The main screening method used for detecting COVID-19 cases is reverse transcriptase-polymerase chain reaction (RT-PCR) testing, which can detect SARS-CoV-2 ribonucleic acid (RNA) from respiratory specimens (collected through a variety of means such as nasopharyngeal or oropharyngeal swabs). While RT-PCR testing is the gold standard as it is highly specific, it is a very time-consuming, laborious, and complicated manual process that is in short supply. Given the high tropism of COVID-19 for respiratory airways and lung epythelium, identification of lung involvement in infected patients can be relevant for treatment and monitoring of the disease. Keeping

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this in mind, both clinical and AI community have shown a lot of interest in using Chest X Ray and CT scans to identify .

Currently, radiological societies (Fleischner Society, SIRM, RSNA) [3], [4], [5] do not recommend routine use of imaging for COVID-19 diagnosis. However, it has been widely demonstrated that, even at early stages of the disease, Chest X-Rays (CXR) and computed tomography (CT) scans can show pathological findings.Chest X-ray can be a useful tool, especially in emergency settings as it can help exclude other possible lung damage and allows for a rough evaluation of the extent of lung involvement. most importantly can be obtained at patients bed using portable devices.Because of their mostly peripheral distribution, subtle early findings on CXRs may be a diagnostic challenge even for an experienced radiologist.

In the recent past, deep learning methodologies have come to aid. They can help in particular for identification of the more subtle findings that could escape the human eye, so that false-negative can be reduced. Several research groups like [4] [9] have used previous knowledge of detecting pneumonia using deep learning models and applied it to diagnose COVID-19. However, one thing that is common to most of the research done on classification models is that they try to tackle the issue of low contrast and blurring in CXR images only through the lens of only spatial domain. In this paper we evaluate the effect of spatial domain enhancements (Histogram Equalization,Negative Transform, Bilateral filter, Gaussian filter, Edge Canny) in conjunction with frequency domain filters (low pass, high-pass, band-pass) on the classification models to diagnose COVID-19. Two models were created by fine tuning VGG16 and ResNet50 architectures and were trained using dataset created from five different sources to study the effects of image enhancements.

2 Related Works

Motivated by the need for faster interpretation of radiography images, a number of AI systems based on deep learning21 have been proposed and results have shown to be quite promising in terms of accuracy in detecting patients infected with COVID-19 via CRX [9] [3][2][4]. Many approaches have been taken to tackle the problem of classifying chest Xray scans to discriminate COVID-positive cases [8]. For example,Sethy et al., one of the first poeple,compare classification performances obtained between some of the most famous convolutional architectures [7]. A transfer learning-based approach was used by them to extract features from images. Then, they trained a SVM on these "these features" to the COVID classification task. Narin et al. make use of resnet-based architectures and the recent Inception v3 and then they use a 5-fold cross validation strategy [5]. Wang et al. propose a new neural network architecture to be trained on the COVID classification task [9].

These works present some potential issues to be investigated:

- Transfer learning: It is widely recognized that transfer learning-based approaches prove to be effective, also for medical imaging [3]. If not implement properly or contains biases, then there can be cascading affects.
- Hidden biases in the dataset: most of the current works rely on very small datasets, due to the limited availability of public data on COVID positive cases. Besides this, there are other biases have to be looked upon. For example, every CXR can have its own image acquisition settings that classifier model should learn to discriminate.

Sa'dah et al work on "Exploiting Hybrid Methods for Enhancing Digital X-Ray Images" was one of the primary inspiration for this work. This paper presents a novel hybrid method for enhancing digital X-Ray radiograph images by seeking optimal spatial and frequency domain image enhancement combinations [6].

3 Methods

In this section, the deep learning approach used is discussed, which based on quite a standard pipeline, namely chest image pre-processing which included re-sampling of the data, data augmentation,image enhancements and finally followed by classification model obtained with transfer learning. Heavy preprocessing was done on the data sets due imbalances in between images of each class. So, first dataset creation will be discussed.

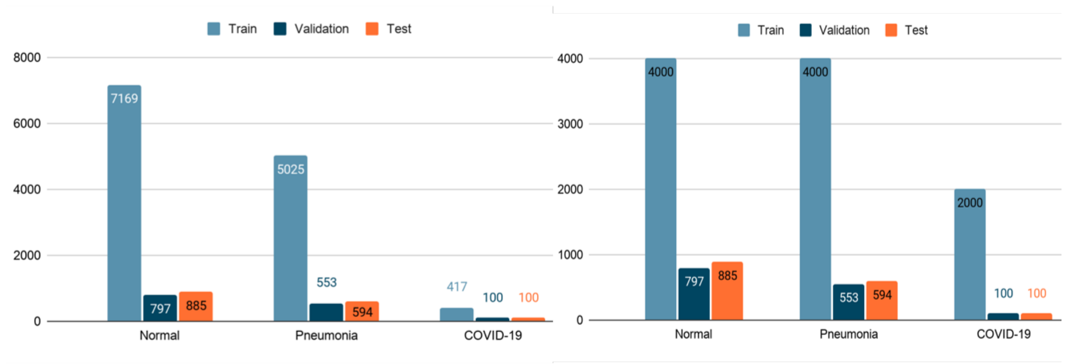


Figure 1: A) Initial Data set Distribution B) New Distribution

3.1 Dataset Creation

The dataset used to train and evaluate the proposed models comprise a total of 13,975 CXR images. The dataset was generation by combining and modifying five different publicly available data repositories. The dataset was created with the help of work done by Wang et al, who have accumulated the links for the available opens source repositories to single location[9]. The provided script in the their research's GitHub , helps to create the dataset with some required modifications and can be found here.

The five repositories used are:

- RSNA Pneumonia Detection Challenge
- COVID-19 Chest X-ray Dataset Initiative
- Actualmed COVID-19 Chest X-ray Dataset Initiative
- COVID-19 Image Data Collection [1]
- RSNA. COVID-19 radiography database.

The initial Dataset distribution can be seen on 1 for this project after creating it from modifying the five open source data repositories listed above. The most noticeable trend that you can notice from these graphs is the limited amount of COVID-19 infection cases and associated CXR images, which reflects the scarcity of COVID-19 case data available in the public domain. Also highlights the need to obtain more COVID-19 data improve the dataset. More specifically, the dataset contains 617 CXR images from COVID-19 cases. For CXR images with no pneumonia and non-COVID19 pneumonia, there are significantly more patient cases and corresponding CXR images. So, there are a total of 7966 patient cases who have no pneumonia (i.e., normal) and 5,538 patient cases who have non-COVID-19 pneumonia. For a deep learning model to be effective, Balancing the training data is extremely important. Unbalanced data favor biases in the learning process. Next, balancing of data is addressed in a number of ways.

3.2 Tackling Imbalanced Dataset

- **Over-sampling and Under-sampling:** The minority class, which is COVID-19 images were over sampled using Synthetic Minority Oversampling Technique. This technique works by synthesizing elements or samples from the minority class rather than creating copies based on those that exist already. This method of oversampling is to avoid model over-fitting.Then, Random undersampling was done to randomly delete records from the majority classes.
- **Data Augmentation:** Data augmentation was done to create transformed version of COVID-19 images (such as flipping, small rotation, adding small amount of distortions). This was mainly done to again avoid overfitting duty oversampling done previously.
- **Class Weights:** Since the goal is to identify COVID positive, and we don't have very many of those positive samples to work with, a classifier with heavily weighting the few examples

that are available is needed. So a keras weight was assigned for each class. These will cause the model to "pay more attention" to examples from an under-represented class(i.e. COVID-19).

3.3 Image Enhancement System

All the images went through Image enhancement system, shown in Figure2 to result in a more suitable image for classification. To understand the effect of different enhancement techniques on the classification, combinations of spatial and frequency domain filtering were applied on the images. First, all the images were first subjected to two contrast image enhancement in spatial domain which are Histogram Equalization and Negative Transform. Then the images went through a combination of denoising and sharpening techniques through bilateral filter, Gaussian filter, and edge canny detection in spatial domain. They also been subjected low, high and band pass filters in frequency domain. After going through contrast and denoising steps, the images were resized to feed them into our classification models.

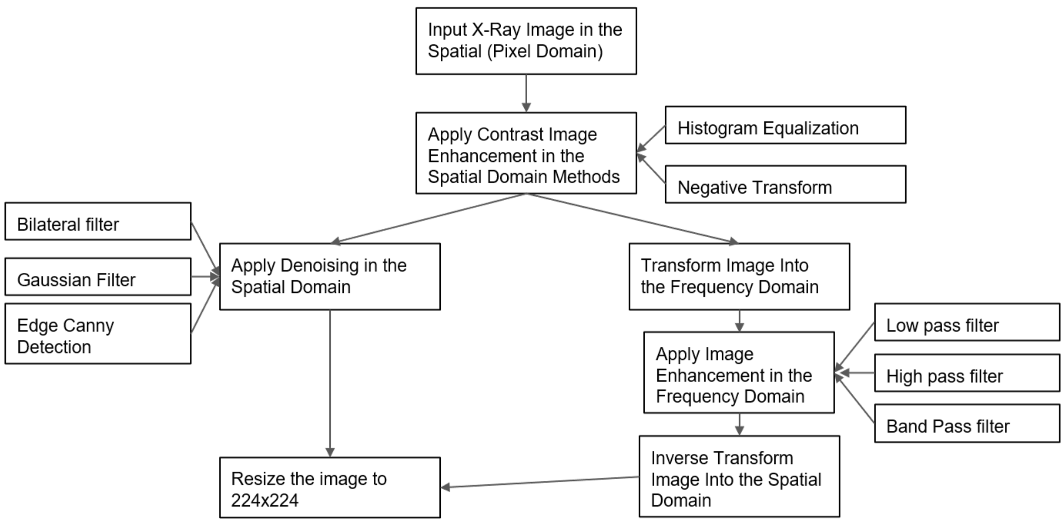


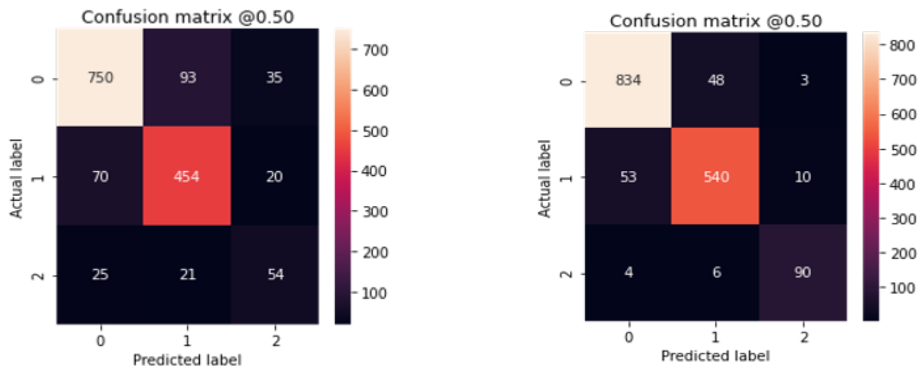
Figure 2: Block diagram of the proposed X-ray radiography image enhancement system.

3.4 Classification Models: Transfer Learning

To overcome the limited data sizes, transfer learning was used to fine-tune two popular deep learning architectures: VGG16 and ResNet50.When performing fine-tuning, the head of the network was first removed and a new Fully Connected(FC) layer head was randomly initialized in a new network and then, connected to the body of the original network. The Convolution layers have already learned rich, discriminative filters, while the FC layers are brand new and totally random. So to circumvent the problem of the gradient being back-propagated from these random values all the way through the network, all layers in the body of the network, except for the new FC layers were froze. The models were then trained with different combinations of the image enhancements for 20 epochs with early stopping callback to avoid overfitting. The loss function used was Category Cross Entropy with Adam optimizer and a learning rate of 0.001.

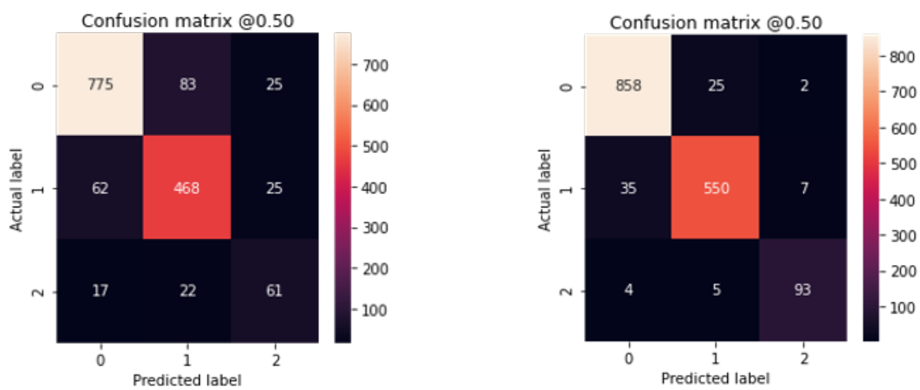
4 Results

The classification results of images trained via VGG16 model shows that the best case was one the images went through data augmentation, had adjusted class weights and were enhanced through Histogram equalization. Although accuracy was more than 90% for best case, it cant be relied upon since the test data contained a lot more normal and pneumonia images. The sensitivity and specificity are greater that 90% so that is a good sign. On average the classifier performed better when images were enhanced with frequency filters than spatial filters.Even ResNet50 had similar trends as VGG16 with histogram equalization with frequency filters performing the best.Even though they have similar trends, from Table 1,2, 3, ResNet50 out performs VGG16 by atleast 1-2% in every metric.



A) B)

Figure 3: Confusion Matrices for VGG16 with 0,1,2 labels representing Normal, Pneumonia and COVID-19 respectively. A) Worst Case: No Data Augmentation, No Adjusted Class weights,No Image Enhancement B) Best case: with Data Augmentation, Adjusted Class weights Histogram Equalization, and Low Pass filter



A) B)

Figure 4: Confusion Matrices for ResNet50 with 0,1,2 labels representing Normal, Pneumonia and COVID-19 respectively. A) Worst Case: No Data Augmentation, No Adjusted Class weights,No Image Enhancement B) Best case: with Data Augmentation, Adjusted Class weights Histogram Equalization, and Low Pass filter

Table 1: Metrics for Best case

Metric	VGG16	ResNet50
accuracy	0.912	0.941
precision	0.903	0.925
recall	0.891	0.912
AUC	0.976	0.978
sensitivity	0.902	0.928
specificity	0.951	0.972

Table 2: Average Metrics for Spatial Filters

Metric	VGG16	ResNet50
accuracy	0.852	0.862
precision	0.855	0.871
recall	0.846	0.858
AUC	0.938	0.957
sensitivity	0.842	0.859
specificity	0.921	0.931

Table 3: Average Metrics for Frequency Filters

Metric	VGG16	ResNet50
accuracy	0.871	0.881
precision	0.868	0.885
recall	0.859	0.874
AUC	0.943	0.67
sensitivity	0.861	0.875
specificity	0.935	0.939

5 Conclusions

The paper presented hybrid methods for enhancing digital X-ray images for improving CNN models in classification of COVID-19.Selected methods from the spatial and frequency domains have been combined to give the best possible enhancement compared to the original image. In future, an end-to-end solution must be developed to optimize the enhancement techniques automatically by the deep learning model.

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