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RESEARCH ARTICLE

DETECTION OF COVID-19 PNEUMONIA EFFECTS IN CHEST X-RAYS USING DEEPLEARNING

Mohammed Khamees Ahmed[1]
[1] Institute of Graduate Studies, Altınbaş University, Istanbul, Turkey
algenan3@gmail.com ORCID: 0000-0001-9145-1939

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Abstract: The development of technological tools based on artificial intelligence (AI) could contribute significantly in the fight against COVID-19. AI is the ability of a machine to apply human cognitive functions. In this paper we propose a deep learning based model for COVID-19 detection relying on the effects it yields on the lungs.

Keywords: MRI, XRAYS, COVID-19, Deep learning, svm

1. Introduction

More than one million persons have pneumonia hospitalization, and over 50, 000 die of pneumonia every year in the USA alone (Koo et. al., 2018). Presently, chest x-rays or films are the best way to diagnose pneumonia (Hansell et. al., 2008) and serve an essential role in clinical and epidemiological treatment.. However, detecting pneumonia on radiographs is a difficult task that depends on the availability of radiologist specialists, so there is a wide opportunity to help specialists with new Artificial Intelligence technologies to facilitate their work and improve the health system. As mentioned above, chest film is used in the screening and diagnosis of many diseases of the lungs. A large number of radiograph studies and radiological reports are typically stored in the PACS (Image Archiving and Communication System) systems of hospitals. A good deal of research has been done to take advantage of the knowledge contained in these databases, but there is a very specific challenge: medical records are often loosely labeled and do not contain annotations. This means that the x-ray is associated withthe diagnosis of the specialist doctor -as negative (healthy patient) or positive (identifying the disease). But the radiograph does not contain delimited the region of the image that led him to such a conclusion or diagnosis. So recent research has focused on exploiting these data sets with deep learning paradigms, which require large amounts of data or images, building large-scale CAD systems for medical purposes. Detecting chest diseases and especially pneumonia on x-rays can be difficult for the specialist.

2. Materials
2.1. COVID-19

Currently, the globe is experiencing the um novo coronavirus pandemic, the serious acute coronavirus syndrome 2 or the SARS-CoV-2, known as COVID-19having its first reported case in Wuhan, China, not the end of the year of 2019. Due to its rapid dissemination, it has become a serious problem of public health in the world. In order to diagnose COVID-19, or test that is being used, but due to its lack in some locations and a delay in obtaining the results, it becomes necessary to identify and develop ferments that can help you professionals A number of alternatives to aid in the identification of COVID-19 and the use of chest radiography, which shows characteristics similar to other pneumonia caused by other coronaviruses In the meantime, a rapid radiological interpretation of images is always available, particularly where we have few resources that pneumonia (caused by viruses and bacteria) has a higher incidence and higher mortality rates. The process of interpreting agents (brain tumors or lung anomalies, for example) is a complex activity and, therefore, is necessary, or the use of image processing techniques, often combined with machine learning techniques, to identify applications of deep learning techniques (deep learning) to classify images of x-ray images and a considerable growth in recent years. Several investigations address this topic, such as performing the classification of images to help prevent early diagnosis of tuberculosis, and classifying injuries through chest radiography also used for classifying x-ray images of the x-ray with pneumonia and other injuries.

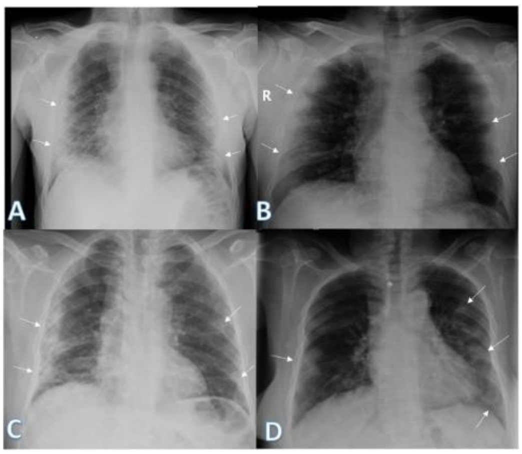

Figure 1. *Effect of COVID19 in Xrays*

2.2 Deep Learning

The deep learning paradigm is a sub-area of machine learning that addresses or automated learning, being carried out through the use of successive deep layers within a neural network architecture. Asa result, each litter passes or the result of its learning for the next litter. The greater the quantity of litters, the deeper the neural network becomes. A main characteristic of deep learning is the use of litters to perform the extraction of characteristics and classification of two dice. As a result, deep learning algorithms have become viable options for image classification tasks, for example.

Deep Learning is a machine learning approach, a branch of artificial intelligence, allowing computers to resolve issues that they would otherwise be impossible to solve. Although a systematic method to deep networking was available since the 1980s, it could not be expanded into large networks and research from neural networks entered a spell of slumber. Hinton GE et al. (Ooi et. al., 2004) showed that deep neural networks could be efficiently trained using a state-of-the-art result of handwritten MNIST digit data set from 2006.

3. Proposed Method

The methodology provided here is a multiple classification issue, as the X-ray picture is identified and classified in 8 potential groups or disorders. We use the ChestX-ray8 data and train it using a convolutionary network to do the ranking and get a model after a number of subtle changes, such as weight loss or weight elimination and L2 regularization, among others. One of the main issues with learning when dealing with data sets, such as those employed in this research, is training. Data increase (A.D.), which generates extra training information from existing samples, is a commonly used approach. Apply a variety of random changes that yield plausible visuals to these samples. The data enhancements procedure may dramatically minimize validation loss, in which both identical convolutionary networks display the graph with training and validation data, one without data enhance and the other with this method. Data increase clearly addresses the overtraining issue on the left side of the picture, in which it is noted that the value of the loss function lowers with validation data first and then grows again. While the training data continues to diminish. The right side of the picture depicts, amongst other ways, how validation loss may be regularized by adding data. There are two dual-head cameras and both per- and inter-critical exams are taken on the same camera.).

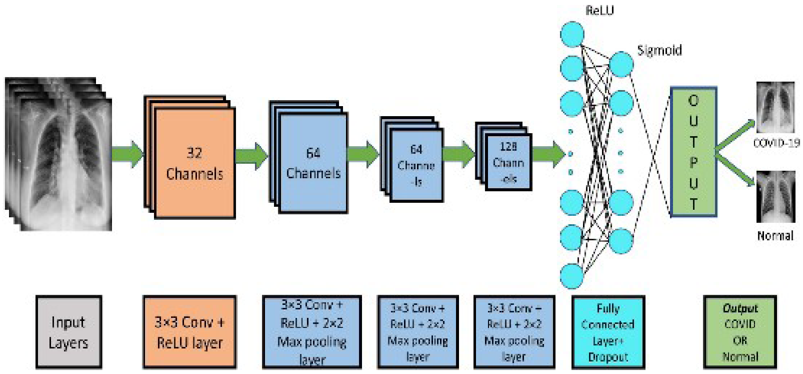

Figure 2. *CNN architecture*

As we shall see in the following section, however, if data enhancement procedures are performed without respect to picture quality, some bad training examples may lead to a less than optimum model of the convolutionary network. In several computer vision applications, the data increase strategy has shown to be an effective strategy; nevertheless, as we see in the next section, some crucial considerations are taken when applying this procedure to medical imaging. The difficulty occurs because certain photos in the data collection are poorly quality, which might influence the training and create a sub-optimal model. These models may create a huge number of false positive or worse ones, as the authors extensively demonstrate in (Ajlan et. al., 2014), and misclassify a new test sample. Theauthors of this research used a battery of testing, in which they assessed the performance of certain famous networks such as VGG16 and GoogLeNet utilizing imagery changed with several sorts of aberrations in picture quality: compression, poor contrast, blurry and Gaussian noise. The scientists observed that the networks are compression-resistant, but are heavily influenced by the other three.This has led to a lot of study in this field, with some studies focusing on the implications these distortions have on the quality of picture for various computer vision tasks based on deep learning networks (Kanne, 2020). This is particularly important for medical imaging, especially with ChestX-ray8, which includes 108,948 frontal radiographs of 32,717 unique patients, collected between 1992 and 2015, with eight common diseases obtained by the use of natural language processing techniques for the mining of radiological reports. As far as we know, no assessment has been carried out in prior studiesusing this data set, including a high number of low quality photos, as seen in Figure 4, which is presumably introduced by the method the authors produced the data set. Some of the photographs have very little contrast, while others are not focused or lack clarity, others are very saturated. The second contribution in this paper is to do an image quality evaluation in addition to the above mentioned data increase technique to decide if the example training may be deemed a suitable candidate for the data enlargement phase and beyond. Training phase processing. Some issues for the assessment of picture quality and the methods used to evaluate it.

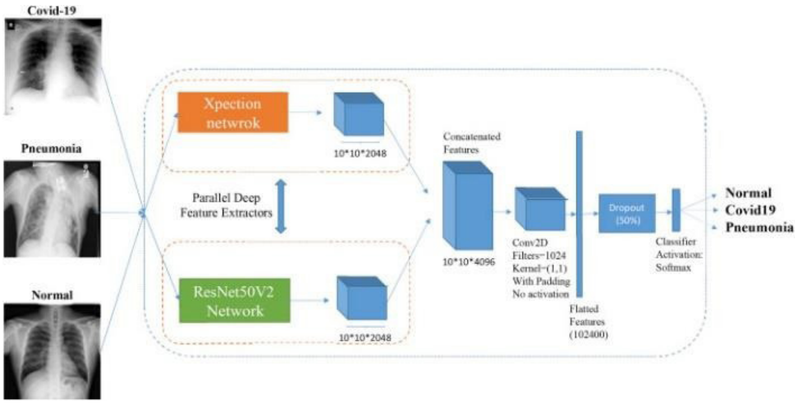

Figure 3. *Proposed Network detection*

As previously indicated, the quality of the input pictures may greatly impair the performance of convolutive network models; the authors of (Ajlan et. al., 2014) undertook tests of Gaussian noise, blur, compression and poor contrast. Even for minor degrees of noise or blur, network accuracy reduces dramatically, and the combination of multiple of these visual defects can only yield worse results. Thus, in this paper, we are implementing a 'filter' or selection process based on several classic image processing metrics1, in order that an image may or may not be considered for post-processing, such the SNR., the black index and the image variance to determine the contrast. These metrics are often correlated: A high noise picture has poor contrast and excessive blurring.

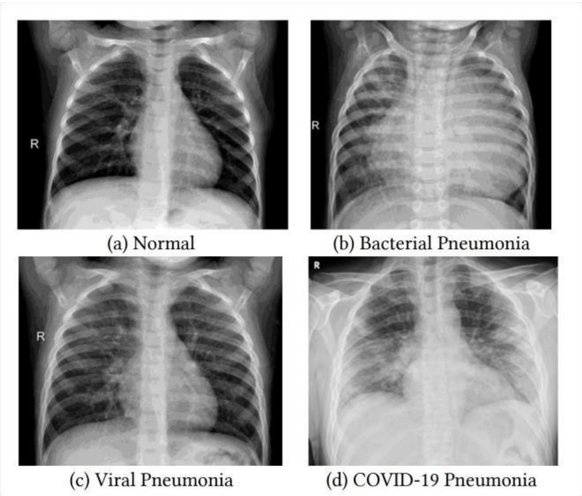

Figure 4. *Input images for training the model*

4. Results

To evaluate the results, the metrics of Accuracy, Precision, Revocation, F1-score and confusion matrix were used. The confusion matrix is generally used in machine learning, having information about the real and predicted classifications performed by a classifier In a confusion matrix the lines are real values in each class, while the columns are the predictions made by the model. The values obtained from the confusion matrix are also used to generate some extremely important metrics for the evaluation of the models, such as: Accuracy, Precision, Revocation and F1-score These metrics are commonly used in the evaluation of learning models From the results obtained, it is possible to see in Figure 3 the performance of the generated models, in the training and test stages. The analysisparameter used was the accuracy per season, that is, the success rate in each season. Proposed CNN-SVM achieved a faster convergence than InceptionResNetV2, both in the training stage and in the test. It is worth noting that there was a discrepancy between the curves in the test stage, which shows that the Proposed CNN-SVM achieved a better performance.

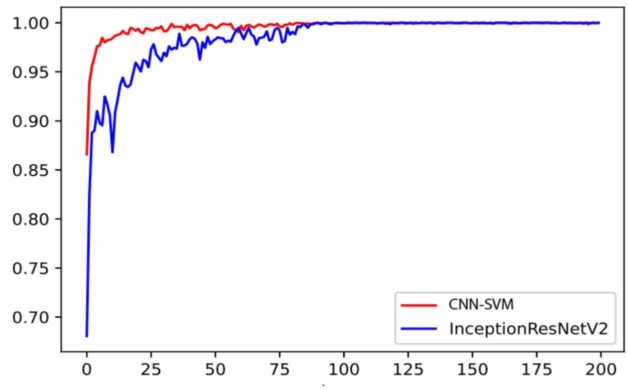

Figure 5. *CNN-SVM vs RESnet Accuracy*

In figure 4.8 it is possible to see the results of precision, recall and f1-score for each class for each architecture. For all classes and metrics, the Proposed CNN-SVM achieved the best result. With this, the Proposed CNN-SVM model is able to not confuse the classes (precision) and is able to find the largest possible number of images of each class (recall). The f1 score is the weighted average of the two metrics:

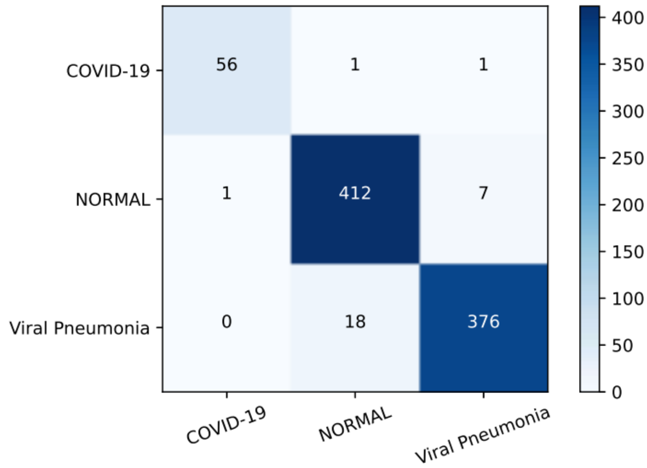

Figure 6. *F1 score of the CNN-SVM detection*

5. Conclusion

Based on the results achieved, we can observe that the model generated through the Proposed CNN-SVM architecture obtained the best performance in the diagnosis of COVID-19, the focus of this study. In all the metrics analyzed, Proposed CNN-SVM obtained a result superior to InceptionResNetV2. Because it achieves a higher hit rate (accuracy) than InceptionResNetV2, Proposed CNN-SVM becomes a feasible choice of architecture to be further explored in future works.It is important to emphasize that this study has as its premise to serve in the future as an alternative way of screening patients. From this study, new possibilities can be explored. A WEB system can be developed in order to serve as a test environment for the model that was trained, that is, the user will be able to upload an x-ray image of the chest of a patient with suspected COVID-19 and the model will generate a possible pre-diagnosis of the image. As a way to optimize and improve the previous proposal, it will be necessary to use more databases containing images of patients diagnosed with COVID-19 or other diseases that can be diagnosed through x-ray images, to enhance and generalize the model.

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