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Convolutional Networks Applied To X-Ray Images for Disease Classification

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Abstract **-** This project seeks the implementation of convolutional networks for detecting the most prevalent pathologies in Mexico in X-ray images. To achieve this, a database was obtained with images labelled in four different conditions: healthy, viral pneumonia, lung opacity, and COVID-19. In the second stage the training and validation of a neural model based on convolutional networks was performed. It was verified that the algorithms based on convolutional networks can be used for biomedical applications, which could reduce the time spent to achieve an automatic pre-diagnosis of some pathologies with high precision.

Keywords**:** Convolutional networks; artificial intelligence; X-ray images; COVID19.

1. Introduction

Currently, technology in hospitals has improved the quality of imaging studies for disease detection or even achieving more specificity in some types of treatments, such as cancer, for example [1]. Computer vision is a technique that has been studied since 1959 and is based on the detection and classification of images by computer [2, 3]. In recent years, these concepts have been applied to the classification and detection of lesions and diseases in medical images to make their diagnosis more efficient [4-6]. Various neural models and algorithms can be used for this purpose, but convolutional networks that achieve deep learning have shown the best results [7]. Additionally, specific algorithms and techniques have been developed for processing medical images, such as segmentation, edge detection, pattern recognition, and feature extraction. These techniques allow for a more precise and automated analysis of medical images, facilitating the diagnosis and treatment of patients [8]. Furthermore, the increase in computational capacity has been fundamental for the development of computer vision, as the processing of medical images requires many calculations and analyses, and advancements in computational capacity have allowed these processes to be carried out more quickly and efficiently. Likewise, the availability of large datasets of medical images has been crucial for the development of computer vision algorithms [9].

Recently, the goal has been to achieve the highest possible accuracy in deep learning classification to ensure an automatic pre-diagnosis of certain pathologies. Some of the recently reported ones include cancer [6], detection of brain lesions [10] or ovarian lesions [11], pathologies detectable by chest X-rays such as cardiomegaly, infiltrations [5, 7, 12, 13], or pneumonias (such as those caused by the SARS-COV2 coronavirus [14], among others).

In this project, the training and validation of a pre-trained convolutional network were carried out for the classification of X-ray images presenting four different conditions: healthy, viral pneumonia, lung opacity, and COVID-19. This convolutional network algorithm can be implemented as a tool for the automatic pre-diagnosis of these pathologies, thus reducing the time required to issue a diagnosis.

2. Methodology

2.1. Database Description

For the training of the network, a pre-existing database [13] containing chest X-ray images labeled as shown in Table 1 was used. In addition, you can see a sample of the images contained in the database in each of the labeled classes.

Table 1. Number of Images in the Database

Class	Number of training images	Number of validation images	Total
Normal	10,000	192	10,192
Lung opacity	1,300	4,712	6,012
Viral pneumonia	1,300	45	1,345
COVID19	1,300	2,316	3,616

2.2. Neural Network Training and Validation

The training was carried out using a deep learning convolutional network to classify the images described in the previous section. For this, AlexNet, a pre-trained model, was used to facilitate the neural network's learning process, which has demonstrated relatively high accuracy for this type of classification [14].

The training and validation phase was conducted using the Deep Learning Toolbox in Matlab®, where the pre-trained network was loaded, the database images were assigned, and the model was trained and validated for a maximum of 30 epochs. Initially, training was performed to identify images belonging to a healthy subject and an ill patient (with any of the three pathologies in the database). Subsequently, a second network was trained to classify the three diseases separately, with training up to a maximum of 50 epochs. The process of the algorithm that can be used for the issuance of a prediagnosis, where convolutional network 1 refers to the classification between sick and healthy and convolutional network 2 to the classification of the three different pathologies.

For the analysis of results, a confusion matrix was created, and the following metrics were obtained from it:

$$precission = \frac{VP}{VP + FP} \tag{1}$$

$$recall = \frac{VP}{VP + FN} \tag{2}$$

$$F1 = 2 \cdot \frac{precisión \cdot recall}{precisión + recall} \tag{3}$$

Where: VP are true positives, FP are false positives, and FN are false negatives, values that can be obtained from the confusion matrix.

3. Results

The training and validation process was carried out with the Matlab® deep learning toolbox, which also provided the accuracy and loss graphs. They indicate that before the first 10 epochs, validation fluctuates between 20% and 80% accuracy, but after this, it trends upwards, reaching a final accuracy of 81.12% after 30 epochs. Similarly, for the training database, a similar behavior is observed, reaching an accuracy of 87.50% at the end of epoch 30. Additionally, the loss graph shows an asymptotic trend towards zero during validation, which rules out overfitting.

The accuracy and loss graphs during the training and validation phase of the convolutional network 2 show that the accuracy increases as the epochs increase, which demonstrates that the neural model is training correctly. In this case, at the end of epoch 50, 81.9% accuracy was obtained. On the other hand, the loss plot shows again an asymptotic behavior at zero before epoch 40 suggesting that the training should be performed maximally until this epoch to avoid over-training of the network.

After completing the described procedure, the algorithm for issuing a pre-diagnosis was applied to all the images in the database. The resulting confusion matrix is presented in Table 2, and the metrics described in the methodology section are shown in Table 3 for each class.

Table 2. Confusion matrix of predictions made by both convolutional networks.

Real class	Predicted class: Normal	Lung opacity	Viral pneumonia	COVID19	**Total**
Normal	9,562	420	48	162	10,192
Lung opacity	977	4,373	61	601	6,012
Viral pneumonia	58	2	1,283	2	1,345
COVID19	364	361	47	2,844	3,616
Total	10,961	5,156	1,439	3,609	21,165

Table 3. Precision, recall, and F1-score obtained for each class by both convolutional networks.

Class	**Precision**	**Recall**	**F1-score**
Normal	0.8724	0.9382	0.9010
Lung opacity	0.8481	0.7274	0.7832
Viral pneumonia	0.8916	0.9539	0.9216
COVID19	0.7880	0.7865	0.7872

4. Discussion

The results demonstrate that convolutional networks trained using the AlexNet model can be used as a tool for the automatic pre-diagnosis of the four conditions present in the database, achieving an accuracy of over 80% using both convolutional networks in series. However, further work is needed to achieve the highest possible accuracy. The results are consistent with previous works [13, 14], which conducted a similar study with various pre-trained networks and different types of pathology classification, achieving similar accuracies.

Additionally, the designed algorithm showed higher precision and recall in diagnosing viral pneumonia not associated with COVID-19. In contrast, for the COVID-19 class, the precision and recall were the lowest, suggesting that the algorithm may be more useful in classifying X-ray images belonging to patients with viral pneumonia not caused by the COVID-19 virus. Regarding the F1 score, the normal class ranked second highest, which is desirable since, in healthcare, it is most desirable for a pre-diagnosis to have the highest accuracy in predicting that the image does not belong to a person with a disease.

5. Conclusions

A convolutional network was trained to classify four different conditions in X-ray images: healthy or normal, viral pneumonia, lung opacity, and COVID-19. The results suggest that the designed algorithm for this classification can be used as a pre-diagnosis tool for these diseases, though further work is planned to achieve even higher accuracy. It is worth noting that while the field of computer vision has been improving in recent years, these algorithms can be used as an auxiliary tool in disease diagnosis but are not intended to replace the activity of a medical professional.

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