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Patient Prediction Through Convolutional Neural Networks

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Abstract

This paper presents a methodology for predicting the lung diseases of patients through medical images using the Convolutional neural network (CNN). The importance of this work comes from the current SARS-CoV-2 pandemic simulation where with the presented method in this work, pneumonia infection from healthy situation can be diagnosed using the X-ray images. For validating the presented method, various X-ray images are employed in the Python coding environment where various libraries are used: TensorFlow for tensor operations, Scikit-learn for machine learning (ML), Keras for artificial neural network (ANN), matplotlib and seaborn libraries to perform exploratory data analysis on the data set and to evaluate the results visually. The practical simulation results reveal 91% accuracy, 90% precision, and 96% sensitivity making prediction between diseases.

Key words: Convolutional neural network (CNN), pneumonia, artificial intelligence (ANN), machine learning (ML)

1 Introduction

The Pneumonia is a disease that occurs with bacterial, viral or fungal infections and causes inflammation in the lungs [1]. Early identification of this disease using X-ray images can play an important role in its treatment. The COVID-19 disease caused by the SARS-CoV-2 virus [2], which has emerged in recent years and declared a pandemic by WHO on March 11, 2020, has also been known to be a source of pneumonia. In such a health crisis environment and against a rapidly spreading disease, it is critical to identify patients who carry the virus as quickly as possible. The most common method followed to detect this disease in individuals is Reverse Transcriptase Polymerase Chain Reaction (RT-PCR) tests [3]. However, these tests give late results, are complicated and require manpower. Moreover, the rate of correctly identifying patients who carry SARS-CoV-2 with RT-PCR tests is only 63% [3]. Computed tomography and chest x-ray images are used as alternative ways to identify this disease [4].

The machine learning (ML) has the potential to be very useful in the field of medicine. The latest improvements in image recognition and object detection combined with the digitization of medical records is a huge opportunity in this regard. The use of electronic medical records by health professionals working in offices has increased from 11.8% to 39.6%, almost four times, between the years 2007 and 2012 in the United States alone [5]. Medical images are an important aspect of a patient's medical records and are usually collected and evaluated by medical experts. However, training an expert radiologist takes many years and comes at great financial costs. Moreover the lack of error in evaluation or diagnosis is never guaranteed. Therefore it will be very beneficial for the evaluation of medical images to be done by artificial intelligence models.

The use of artificial intelligent to be trained and used on the data obtained from the visual records of various patients is becoming increasingly common. In addition, the abundance of this data today creates a suitable environment for the development of different machine learning models. A CNN can be retrained with a relatively small amount of data thanks to the transfer learning technique, in which the neural network previously trained for another task is retrained for a similar task using the same weights [4]. Transfer learning technique was used by Vikash et al. [6] for the detection of pneumonia on pre-trained ImageNet models [7]. Rajpurkar et al. [8] trained an 121-layer deep CNN on chest x-ray images and detected 14 kinds of different lung diseases, including pneumonia. Sundaram et al. [9] obtained an area under curve (AUC) value of 0.95 in a pneumonia task using the AlexNet and GoogLeNet models using image augmentation technique. Chowdhury et al. [4] investigated the role of artificial intelligence in the diagnosis of viral pneumonia and COVID-19. In their research, they have carefully selected and compiled from various datasets and created a public database to train machine learning models in the diagnosis of COVID-19 [10]. Using the transfer learning method, they were able to obtain 99.7% accuracy, 99.7% accuracy, 99.7% sensitivity and 99.55% specificity, despite the limited number of data. Ker et al. [11] investigated the role of deep learning in the analysis of medical images in the health sector. In their research, they explained key issues such as classification, detection, segmentation, and talked about the obstacles and opportunities for the future of deep learning in medicine. Maguolo and Nanni [12] and Tartaglione et al. [13] argued that positive COVID-19 diagnoses using deep learning methods on x-ray images cannot actually suggest the presence of the disease. Also, the studies of Albawi et al. [14] have been very helpful in understanding Convolutional Neural Networks, in which the structure of these networks were explained effectively.

Today, artificial intelligence is already used extensively in the diagnosis of brain tumors, cancer and heart diseases [15, 16, 17, 18, 19, 20, 4, 21]. This work employ the CNN to capturing and considering the included infections in lungs of patients through X-ray images that is not straightforward to see by the human eye. This type of network is selected due to its capability in improving the image quality obtained from a high-speed, and a low-light video endoscopy. The remained of this work is as following: Section 2 describes the presented method in this work through machine learning. Section 3 provides the simulation results and finally Sec. 4 concludes this manuscript.

2 Patient Prediction with Machine Learning

The ML is a sub-topic of artificial intelligence. In simple words, according to the definition of Tom M. Michell (1997); If the performance metric P of a computer program increases with experience E with respect to a task T, then that program is said to have learned from experience E of task T, as measured by performance P [22]. This section devotes to describe the presented method though ML leads to predict the lunge diseases through X-ray images. If a given task wants to distinguish which of two or more classes a data belongs to, this task is called a classification task in machine learning. Distinguishing a chest x-ray image as diseased or healthy based on image features is a classification problem.

2.1 Artificial Neural Networks

McCulloh and Pitts [23] described the first artificial neuron in 1943. This idea later evolved into the idea of the perceptron presented by Rosenblatt [24] in 1958. At its core, the ANN is a layer of perceptrons interconnected by inputs and outputs as Fig. 1 presents. The way the human brain learns has significant inspiration on the design of the architecture of artificial neural networks. It can indeed be seen that when it comes to vision, the way that our brains process visual images is accurately mimicked by CNNs [25].

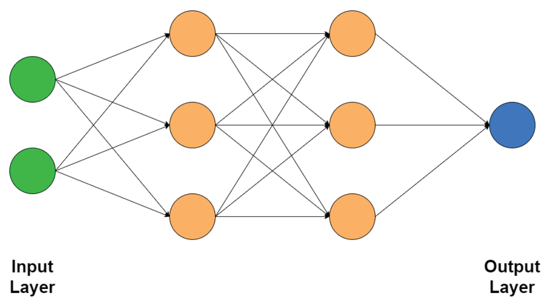

Figure 1: An ANN diagram.

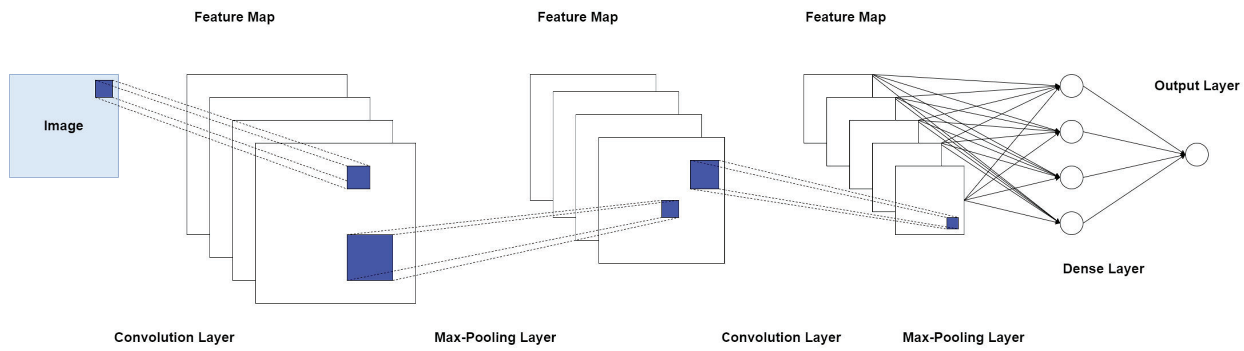

Figure 2: A CNN diagram.

2.1.1 Convolutional Neural Networks

One of the most used types of ANN is the CNN. CNNs were introduced by Lecun et al. where they used it to recognize hand-written digits [26]. Normally, 32x32 neurons are required to receive input from an image with 32x32 pixels. CNNs have sparse neuron connections to avoid this. That is, only some neurons are connected to the input and output [11]. In this way, the features of the image are learned over time. As can be seen in Fig. 2, a CNN first detects low-level features such as lines and edges. The network then with each iteration can extract detail features, and ultimately recognize the whole image.

3 Simulation Results

This section presents the practical simulation results through X-ray images for predicting the infection diseases. The important and first step in starting the simulation is providing the suitable amount of dataset. For this case, the images presented in [27] are used. The selected dataset was collected from Guangzhou Women and Children's Medical Center in China; They are 5,863 chest x-ray films in JPEG file format taken in the routine care of pediatric patients aged one to five years. These data were divided into two classes as "Pneumonia" and "Normal" and the unusable ones (low quality, unreadable condition, etc.) were eliminated. Finally, the available data was examined by 2 experts before being used in any machine learning or artificial intelligence project. In the dataset, there are chest x-ray images in the train, test and val folders, which were also divided into folders of images of their own classes. Sample pictures from both classes are shown in Fig. 3 and Fig. 4. The images in each folder, together with their respective labels, are converted to numpy matrices and assigned to train, test and val variables in 150x150x1 dimensions to establish a standard image size. Then, the attributes (images) and labels in these matrices are assigned to the variables X_train, y_train, X_test, y_test, X_val, y_val, respectively. The pixel values are normalized by dividing the numbers in X_train, X_test and X_val matrices by 255. Finally, X_train, X_val and X_test matrices were reshaped as 5216x150x150x1 as per TensorFlow requirements.

In order to augment the dataset, ImageDataGenerator class from Keras.preprocessing.image library is used. By applying transformations such as rotating the image, zooming in on the image, shifting images vertically or horizontally and flipping the images horizontally, we were able to almost triple the amount of data.

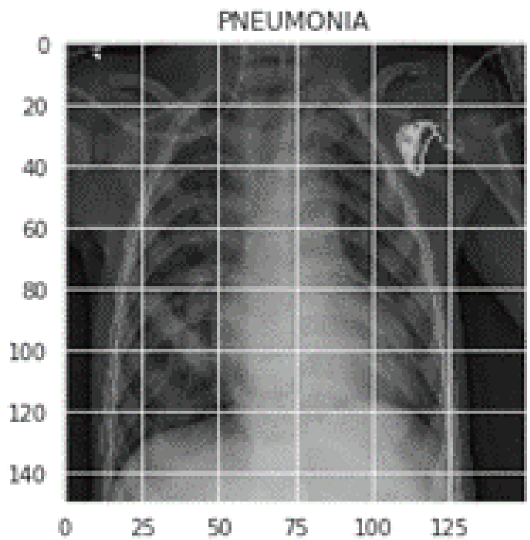

Figure 3: Sample image with pneumonia [28].

After providing the dataset, the coding is written at the Python environment and libraries such as TensorFlow, Keras, Scikit-learn for machine learning algorithms are used. Matplotlib and Seaborn libraries are also used for exploratory data analysis and visualising the results. Each convolution layer

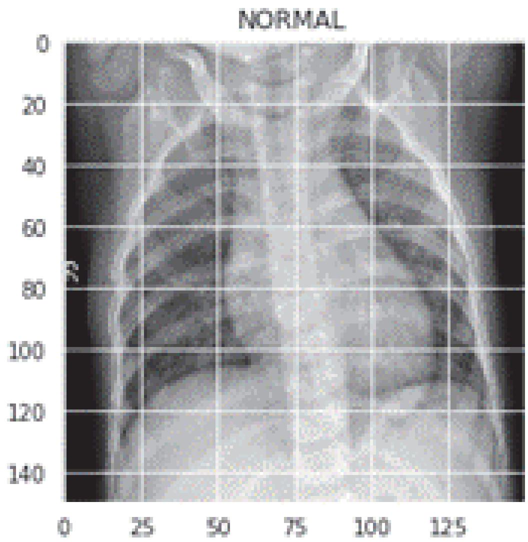

Figure 4: Sample image with healthy lungs [29].

had ReLU activation with and 2x2 max pooling and batch normalization in between those layers. To speed up the training of the model and to prevent overfitting, we made use of the dropout technique. The output matrix is then flattened and connected to a dense layer. Finally the dense layer is connected to a single neuron with a sigmoid activation function to predict the probability of the image belonging to either class.

As Fig. 5 presents, the model has achieved 90.7% accuracy and 0.39 loss. The precision, recall, and f1-scores for pneumonia detected cases are respectively 90%, 96%, and 93%. There were 374 True Positives out of 416 actual positives and 192 True Negatives out of 208 actual negatives.

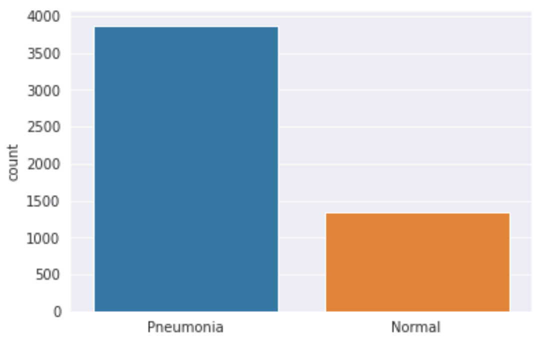

Figure 5: Samples in training set.

4 Conclusion

This work devotes to prove the effectiveness of ANNs and CNNs in chest x-ray images in the early diagnosis of lung diseases, which are becoming more and more widespread with the effect of the SARS-CoV-2 epidemic. The presented method is approached as a binary classification problem as we had to distinguish between healthy cases and cases with pneumonia. For this case, we collect various chest X-ray images for predicting the infections in the patients: distinguish between healthy cases and cases with pneumonia. The simulation results developed in Python coding environment reveals 91% accuracy in the diagnosis of lungs with pneumonia by using a CNN.

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