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Classification of chest pneumonia from x-ray images using new architecture based on ResNet

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Abstract: Pneumonia is a potentially fatal bacterial or viral lung infection. The detection of pneumonia anomalies in the early lungs, can save the life of a child or an old lady, especially, in the early moments;
These divergences have a very minimal size.
In this paper we propose a new architecture based on ResNet 50, we project the adjusted Resnet50 model, based on medical images of the chest to bring out the infected examples with pneumonia. The result predicted are very interesting (97, 65 %) by comparing them with several prior scientific researches and radiologists hope.

Keywords: Chest x-ray pneumonia classification, convolutional neural network, deep learning, medical imaging, ResNet

I. Introduction

Pneumonia is an infection that settles in the lungs. The lungs are filled with fluid and make breathing difficult. It's caused by penetration of thirty different, infectious or annoying germs such as bacteria, viruses or fungi in the space where the gas exchange occurs. [1]

This place must be always clean and free of substances so that it is prevented of air contact with the blood. The most common symptom is coughing with secretion, high fever, chills and lack of air or chest pain during breathing.

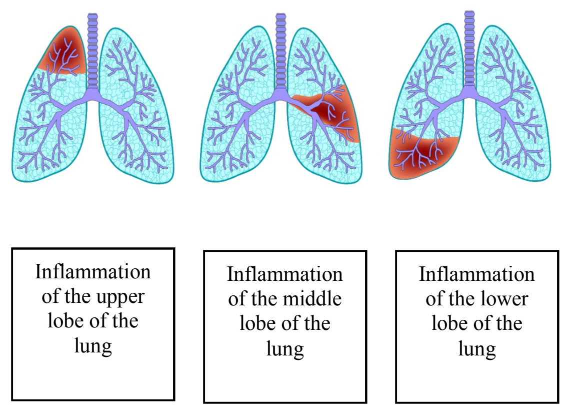

Figure 1: different position of inflammation in human lungs [4]

Morocco is closely concerned since this disease kills several hundred children every day.
In the past 25 years, scientific research has manifested an astonishing upheaval in medical imaging particularly with regard to radiology using x-rays.
Professionals find some important problems when dealing with patients as well as diagnosing them

A band of professionals slows down the diagnosis and treatment process, as patients stay to long waiting. Thus, it generates a workload for doctors. No need to remind us that doctors are still humans, they understandably still makes mistakes.

Therefore, integrating an approved technicality to healthcare system mean a huge medical-social positive impact.

Artificial Intelligence and Machine Learning techniques have revolutionized medical imaging in recent years. For instance, t a deep CNN, called Decompose, Transfer, and Compose (DeTraC), for the classification of COVID-19 chest X-ray images. The experimental results showed the capability of DeTraC in the detection of COVID-19 cases from a comprehensive image dataset collected from many hospitals. High accuracy of 95.12% was achieved by DeTraC in the detection of COVID-19 X-ray images from normal, and severe acute respiratory syndrome cases. [2]

Vikash Chouhan proposed an ensemble model that combines outputs from all pretrained models, which outperformed individual models, reaching the state-of-the-art performance in pneumonia recognition. [3] His model reached an accuracy of

96.4% on unseen data from the Guangzhou Women and Children's Medical Center dataset.

Deep learning enables the creation of end-to-end models to achieve promised results using input data, without extract a manual feature. Pneumonia necessitate the need of expertise in this field. The reason why interest were requested in developing the automated detection systems based on deep learning techniques.

Pneumonia is a big problem that needs to be seriously considered and inspected carefully.

In this paper, we propose 'ResNetChest', a deep learning architecture model for automatic pneumonia diagnosis, requiring chest x-ray images to perform this diagnosis return.

Apart from these significant achievements, CNNs work very well on large datasets. However, most of the time they fail on small datasets if layers ordering care is not taken. ResNetChest obtains a higher detection rate in the diagnosis of the PNEUMONIA using the chest X-ray images.

The rest of article is composed as follow: Section 2 describes the materials and methods with focus on proposed architecture. Section 3 we explain the design of the model. Finally section 4 we summarize the contribution of this work.

II. MATERIALS & METHODS

The following table describes sequentially the different layers that data crosses for a better optimized and convergent learning:

Layer (type)	Output Shape	Parameters
input_1 (InputLayer)	[(None, 128, 128, 3)]	0
batch_normalization	(BatchNo (None, 128, 128, 3)	12
resnet50v2 (Model)	(None, 4, 4, 2048)	23564800
conv2d_2 (Conv2D)	(None, 4, 4, 128)	262272
conv2d_3 (Conv2D)	(None, 4, 4, 128)	16512
flatten (Flatten)	(None, 2048)	0
dense (Dense)	(None, 256)	524544
dense_1 (Dense)	(None, 256)	65792
dropout (Dropout)	(None, 256)	0
dense_2 (Dense)	(None, 256)	65792
dense_3 (Dense)	(None, 256)	65792
dropout_1 (Dropout)	(None, 256)	0
dense_4 (Dense)	(None, 2)	514

Table 1: Layers sequence of described model

The goal of machine learning is to create an accurate model that answers our questions correctly most of the time, for which, we need to collect data to train on. We anticipate and get little percentage of our data to evaluate the model by means of manipulation and adjusting, like duplication, normalization, and/or error correction, etc. Data is collected arbitrarily, chest may be infected with pneumonia or without. We suppose in this paper, that the quality is good enough in front of the model power.

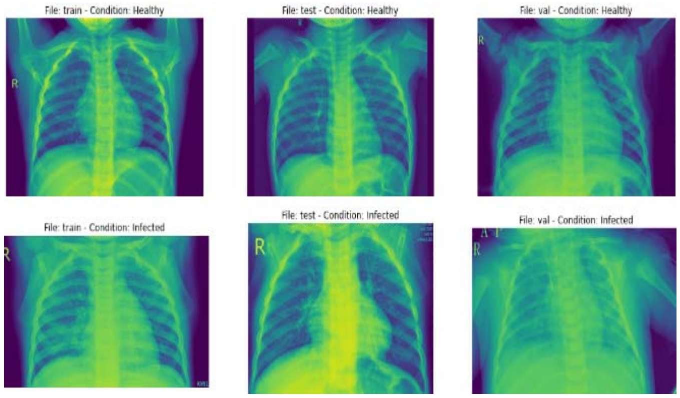

Figure 2: Detecting pneumonia from chest x-ray images in Python

At the first, our input layer is chest x-ray image to a determined output which will be a normal chest or a kind of pneumonia anomalies.
In between, we enumerate some layers ordered as follows:

- We build a deep convolutional neural network based Resnet50 models. [6]
- The parameters are defining the image dimension (128x128)
- In addition we apply a normalization batch which normalize the activation close to 0, the same for the activation standard deviation close to 1.
- ResNet50V2 based on Resnet50 architecture, i.e., is a residual convolutional neural network that is 50 layers deep [7]
- Convolutional layers: consist of bi-dimensional multiplication of a set of weights with the input.
- Convolutional layers; this case is tridimensional.
- We use flatten layer function to simplify an input of shape:

(batch_size, 2, 2) → (batch_size, 4) [8]

- As a fully-connected –layers, we are using dense_1, dense_2, dense_3, and dense_4 to transfer a fully activated neural.
- In a neural network, the activation function is responsible for transforming the summed weighted input from the node into the activation of the node or output for that input.
- Dropout (0.7) is a regularization method that approximates training a large number of neural networks with different architectures in parallel, we retain inputs from the visible layer with 70%. [9]

In our model, we used offline augmentation as pretreatment, which assist us to multiply our train example by as many times as we want.
It can seems a wrong choice applying an offline augmentation, except if announce that with GPU, we will not need an online augmentation, because of full exploitation of our GPU.

ReLu improve the efficiency of the processing by inserting between the processing layers a layer which will operate a mathematical function (activation function) on the output signals [10]

III. Experimentation & Results

A. Pneumonia Dataset

The pneumonia dataset in use in this research through these x-ray images available in public in kaggle which has been contributed for applying our model.

In our input, it's composed about 1.15 GB (Many thousands of JPEG format), decomposed for testing, training and validated parts. [11]

Training set are used to adjust the weights on our model, moment where we use validated set to minimize over-fitting. Testing due is used only for testing the final solution to confirm predictive potential of the model.

B. Performance metrics:

In the script of the model, we used the Categorical Accuracy, which allows us to evaluate the indexes of the maximal true value if they are equals to the index of the maximal predicted one. [12]

The performance of each convolutional neural network implementation is assessed using training accuracy histories

For the quantity, there are several method to increase the data, like some functions easily used from Keras bookstores.
When evaluating a model, we test by changing the image size, the batch size and epochs number. After several tries and setting up some functions. The number of parameters was 24.566.030

We assume that the more we increase the number of epochs, the more learning increases, precision becomes relevant, and we have to choose larger Learning rate.

After a number of observations of existing methods and architectures of CNN, principal model have been chosen, i.e. Resnet50 to train from scratch, while some superposed layers were used to apply fine adjustment, as for error reduction as well as for increasing the precision. [13]

IV. Results

Our model ResNetChest realize 97.65% accurate. After keeping iterating, we totally make this close to 100% accurate, with a lower complexity based number of parameters, i.e. layers iteration.

Network	Accuracy (%)
CheXnet	76.80
CNN with Unmodified Input	63.74
CNN with Expanded Color Scheme	65.42
CNN with Lightened Image on Increased Contrast with ResNet	78.73
ResNet	62.9
ResNet 50 [7]	86
ResNet 50 post-adjusted with layers (our result)	97.65

Tableau 2: Accuracy comparison based used neural network

Basics of Resnet architecture makes power of this model is to counteract vanishing gradient problem: as long as this gradient is back propagated its value does not decease because the local gradient is 1. The ResNet architecture, shown below, should now make perfect sense as to how it would not allow the vanishing gradient problem to occur.
These skip connections act as gradient superhighways, allowing the gradient to flow unhindered. [14]

So, as this gradient is back-propagated, it does not decrease in value because the local gradient is 1.
The ResNet architecture, shown above in the colored schema, how it would not allow the vanishing gradient problem to occur. These skip connections act as gradient highways, allow the gradient to flow unhindered.
Deep learning continues to impress us by disrupting artificial intelligence and solving minute details in our daily life but also continues to disclose other scientific concerns and puzzles not yet put in the light of scientific research.

When running our model, we have found that as the number of epochs increases, in despite of, there are times where the validation accuracy actually decrease, when we train long enough we catch the purpose. The idea is the model won't be able to generate well,
That why we have added regularizer and dropout functions to decrease, and realize the newer knowledge with back propagation concept. [15]

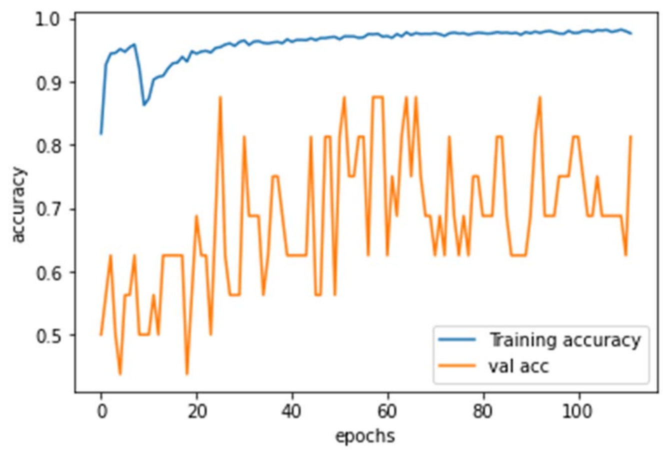

Figure 3: Epochs based Accuracy schema

Schemas above and below, describe how our post layers in front of resnet50 has powerfully occur a pleasing result. [16]
In fact, after each epoch interval level, the val_accuracy increases and the val_loss decreases until get the wind up.

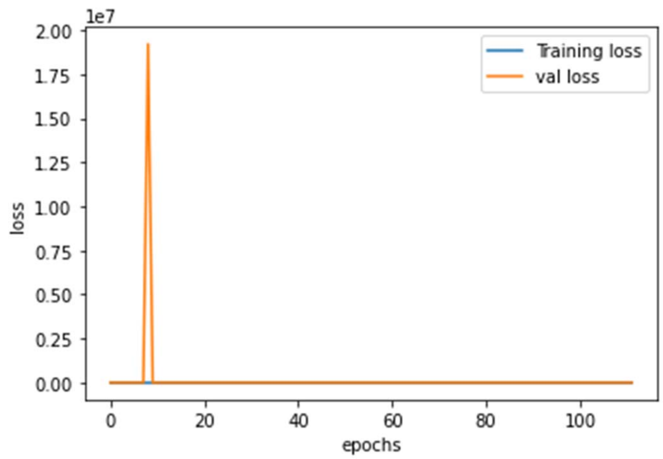

Figure 4: Epochs based Loss schema

V. CONCLUSION:

Every year, 1.8 million children die from pneumonia worldwide, making it the leading cause of infant mortality.
Paramount progress has been made in deep convolutional neural networks for medical image classification.
A high accuracy facilitate detection of physical symptoms earlier.
In our work, we propose a new architecture named ResNet Chest based on medical images of the chest, with an accuracy exceeding 97.65% which assist expert in medicine against this scourge.

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