

DIAG a Diagnostic Web Application Based on Lung CT Scan Images and Deep Learning

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Abstract. Coronavirus disease is a pandemic that has infected millions of people around the world. Lung CT-scans are effective diagnostic tools, but radiologists can quickly become overwhelmed by the flow of infected patients. Therefore, automated image interpretation needs to be achieved. Deep learning (DL) can support critical medical tasks including diagnostics, and DL algorithms have successfully been applied to the classification and detection of many diseases. This work aims to use deep learning methods that can classify patients between Covid-19 positive and healthy patient. We collected 4 available datasets, and tested our convolutional neural networks (CNNs) on different distributions to investigate the generalizability of our models. In order to clearly explain the predictions, Grad-CAM and Fast-CAM visualization methods were used. Our approach reaches more than 92% accuracy on 2 different distributions. In addition, we propose a computer aided diagnosis web application for Covid-19 diagnosis. The results suggest that our proposed deep learning tool can be integrated to the Covid-19 detection process and be useful for a rapid patient management.

Keywords. Covid-19, CT-scan, Deep learning, CNN, Classification

1. Introduction

SARS-CoV-2 disease (Covid-19) is a highly contagious respiratory disease. Early diagnosis of Covid-19 is crucial in reducing the spread of the disease and its mortality. Diagnosis can be based on several methods: clinical symptoms, molecular tests, serology, laboratory examinations and imaging using chest X-ray examination, chest computed tomography (CT-scans) or lung ultrasound [1].

SARS-CoV-2 RT-PCR is the gold standard diagnosis. Although it can be useful to do imaging diagnosis for patients with clinical signs of Covid-19 and negative initial molecular test [2], most of the findings observed in CT-scans are “ground glass opacities”, “crazy paving” and “reversed halo sign” [1].

In pandemic times it is necessary to offer tools to help clinicians’ decision making for quick isolation and appropriate patient treatment. Deep learning in the field of

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automatic diagnosis of different disorders is a rapid solution to support the management process for patients in critical conditions.

Several deep learning-based techniques for classification [3] of patients, segmentation [4] or quantification [5] of Covid-19 lesions have been performed. Classification methods are often binary. Models are mostly trained on X-ray images or CT-Scans, but studies suggest that CT-scans are more reliable compared to X-ray images for Covid-19 diagnosis [6].

Different CNN architectures were investigated and modified versions were proposed with optimization methods to improve model's classification accuracy. ResNet reached the highest detection accuracy of 95% to identify "ground glass opacities" [7]. Meanwhile, DenseNet combined with a machine learning classifier achieved the classification accuracy of 99% [8], and EfficientNet was the best among 15 other CNN classifiers based on the accuracy of 82% [9].

In this work, we aim to develop deep learning models that can detect Covid-19 from CT-scans. We trained and tested 3 CNNs for classifying CT images from 2 datasets using 4-folds cross validation, and verified how well it generalizes to new incoming data from 2 other datasets. We then integrated our best model in a platform intended for clinicians.

The remainder of this work is organized as follows. In Section 2, we first present the details of the datasets used for training and testing our models, then explain our deep learning methods, and finally give a short description of our web application. Experimental results are presented in Section 3. Finally, Section 4 discusses the results and concludes the paper.

2. Methods

2.1. Datasets

We selected 4 available datasets. The first one from Zhang et al. [5] proposed a CT-scan database of 2246 patients including 752 Covid-19 patients. The second dataset proposed by Rahimzadeh et al. [10] contained 2282 CT images from Covid-19 patients and 9776 CT images from healthy patients. Next, the third dataset from He et al. [11] consisted in 349 CT images from Covid-19 patients, and 397 CT images from non-Covid patients. Lastly, the fourth dataset of Soares et al. [12] contained 1252 CT images labelled as Covid-19, and 1230 CT images of healthy subjects.

For the training set we selected datasets [5] and [10] which contain entire CT-scans.

An entire CT-scan consists in a sequence of consecutive slices from the chest, some of which may contain evidence of Covid-19 infection, while others can be healthy. In addition, the upper and lower parts of the lung are not discriminatory for the disease detection. The training set was thus divided into 3 classes: Covid-19, Healthy and Closed lung.

To get a fair approximation of the model a 4-fold cross-validation was used to train and validate the CNNs on [5] and [10]. We thus trained our models on 27000 CT images and tested on 9000 unseen CT images in each iteration. To avoid misleading results, we ensured that all samples from a given patient appear in either the training or the testing datasets, but not in both.

In addition, to investigate the generalization of our models; we evaluated the behaviour of our models with images from two other datasets, namely 746 CT images from [11] and 2482 CT images from [12].

2.2. CNN

We selected deep learning architectures that showed great performance in the state of the art: ResNet50, DenseNet161 and EfficientNet-b7. We fine-tuned each CNN using the weights from the training on ImageNet. The fully connected parts of the models were fixed to 3 prediction nodes layers with Sigmoid activation function.

We scheduled the learning rate using SGD optimizer that we started at 0,001. Batch normalization has also been used to allow rapid convergence of networks. The batch size varied from 8 to 64 depending on the network.

The use of a pulmonary parenchyma mask was tested at every CNN entry, in order to focus the learning on regions containing the features observed during the Covid-19 infection, and not on the meaningless parts such as the vertebral or the axillary region.

2.3. Web Application

We develop DIAG, a Flask web application served with uWSGI and Nginx. Flask architecture contains two important parts: The server side “app.py” preloads the models, operates pre-processing and makes predictions, and HTML file receives Python objects and synthesizes the predictions.

3. Results

In order to evaluate the model’s performance, this study used Accuracy, Specificity, Sensitivity, Precision and F1-score as evaluation metrics.

The test on the datasets [5] and [10] resulted in the highest Accuracy, Specificity, Sensitivity, Precision and F1-score of 92.48%, 94.14%, 89.48%, 90.27% and 89.87% respectively. Tests on [11] led to a decrease in performance. Meanwhile, testing on [12] gave results similar to testing on [5] and [10] with Accuracy rate of 92.03% for ResNet50. Table 1 lists the results of the different CNNs.

Table 1. Evaluation of the models trained during a 4-fold cross-validation on [5],[10], tested on [11] and [12].

Models	Evaluation Metrics (%)	Test set [5], [10] 1 st fold	Test set [5], [10] 2 nd fold	Test set [5], [10] 3 rd fold	Test set [5], [10] 4 th fold	Test set [5], [10] Average	Test set [11]	Test set [12]
ResNet 50	Accuracy	79.02	97.22	97.11	96.58	92.48	84.53	92.03
	Specificity	83.43	97.89	97.80	97.42	94.14	80.35	97.07
	Sensitivity	71.42	95.87	95.71	94.92	89.48	89.26	88.04
	Precision	74.28	95.88	95.77	95.15	90.27	80.15	96.82
	F1-score	72.82	95.87	95.74	95.03	89.87	84.46	92.22
EfficientNet-b7	Accuracy	84.06	96.08	94.79	92.36	91.82	81.73	83.67
	Specificity	87.70	97.02	96.06	94.20	93.75	74.56	87.38
	Sensitivity	77.74	94.22	92.27	88.69	88.23	89.80	80.03
	Precision	79.12	94.31	92.34	89.10	88.72	75.83	86.64
	F1-score	78.42	94.26	92.30	88.89	88.47	82.23	83.20
DenseNet 161	Accuracy	82.40	94.32	97.46	94.58	92.19	79.07	89.46
	Specificity	86.27	95.65	98.09	95.92	93.98	75.31	99.02
	Sensitivity	75.62	91.68	96.20	91.93	88.86	83.29	80.11
	Precision	77.74	91.68	96.22	91.82	89.37	75.00	98.82
	F1-score	76.67	91.68	96.21	91.87	89.11	78.93	88.49

The Grad-CAM (1) and Fast-CAM [13] (2) explanations for ResNet50 with parenchyma mask are shown in Figure 1. We clearly see that the model focuses on the region containing the parts affected by Covid-19.

Figure 1 illustrates also the DIAG procedure for loading a CT-scan and launching prediction (3). The prediction established by the model is shown in (4). The viewer in (5) allows the clinician to verify the predicted diagnosis.

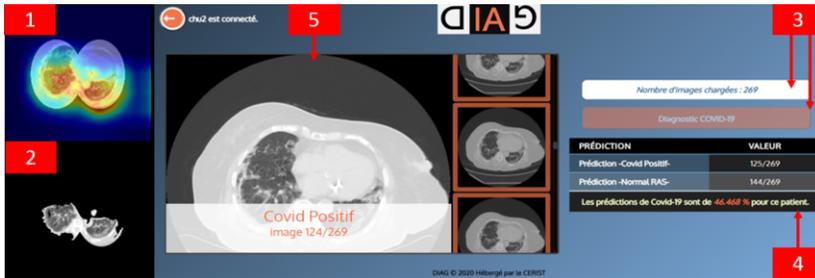


Figure 1. Grad-CAM and Fast-CAM data visualisation [13], and the DIAG platform prediction screen.

4. Discussion and conclusions

In this study, we proposed a deep learning solution for the diagnosis of Covid-19 disease based on CT-scan images. We made a quantitative analysis of different CNNs and qualitatively assessed the obtained models using visualisation algorithms. Finally, we developed a web application to assist clinicians during the diagnosis process.

Testing our models on [12], which contains images acquired with different clinical practices; demonstrated the model's generalizability. Even more, compared to the best proposed approach available in the state of the art [3] our ResNet50 and DenseNet161 models achieved better performance.

Nevertheless, the testing on [11] shows a decrease in accuracy because this dataset contains non-Covid cases including patients with lung infections which have similar features to Covid-19 disease. In addition, images from [11] contain textual information which could have biased the predictions.

Even though the proposed models achieved promising results, there are still some improvements that need to be made. Unfortunately, ResNet50, DenseNet161 and EfficnetNet-b7 models contain respectively, 23.51, 26.47 and 63.79 million of parameters which makes them extremely memory hungry. We prospect to create a CNN with feature extraction based on the ResNet50 backbone design and replace the classifier. The resulting model would have fewer parameters without the fully connected part.

Data from other sources need to be incorporated to achieve better performance. Radiologists intend to add Algerian datasets in future work. Meanwhile, we can use GAN to generate new instances of CT images [14] to continue the networks learning.

The use of the features described by the Fast-CAM [13] can be an interesting prospect to obtain the rendered approximation of the Covid-19 lesions. It would be innovative because the quantification is mainly carried out with the CNNs dedicated to the segmentation [15].

Following the quantification of the disease using the patterns described by the Fast-CAM rendering, we can add a clinical database to retrieve the patient's information and assess the severity of the Covid-19 as proposed in [16].

DIAG can be seen as an end-to-end solution that can store CT images, improve model's performance and provide more accurate diagnosis. Nonetheless, there should be a patient's medical data management, with particular regard to the CT-scans anonymization and the access control.

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