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USE OF DEEP LEARNING TO DIAGNOSE COVID-19 BASED ON COMPUTED TOMOGRAPHY IMAGES

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ABSTRACT

The newly identified Coronavirus pneumonia, later called COVID-19, is highly transmissible and pathogenic. The most common symptoms of this disease are dry cough, sore throat, and fever. Symptoms can progress to a severe form of pneumonia with critical complications, including septic shock, pulmonary edema, acute respiratory distress syndrome, and multiple organ failure. A major obstacle in controlling the spread of this disease is the inefficiency and scarcity of medical tests. Increasing efforts have been made to develop deep learning (DL) methods to diagnose COVID-19 based on tomography images. These computer-aided diagnostic systems can assist in the early detection of abnormalities in COVID-19 and facilitate the monitoring of disease progression, potentially reducing mortality rates. In this study, we compared the popular resource extraction structures based on deep learning for the automatic classification of COVID-19. To obtain a more precise method, which is an essential learning component, a set of deep convolutional neural networks (CNN) was chosen to train our model. The performance of the proposed method was validated using a COVID-19 dataset with computed tomography (CT) images. This dataset is available to the public and contains hundreds of positive CT scans for the disease. DL methods were performed and the best classified CNN was able to achieve excellent diagnostic results for COVID-19.

KEYWORDS: Convolutional Neural Network, Transfer Learning, COVID-19, Tomography, Dataset.

USO DA DEEP LEARNING PARA DIAGNOSTICAR A COVID-19 COM BASE EM IMAGENS DE TOMOGRAFIA COMPUTADORIZADA

RESUMO

A recém-identificada pneumonia por coronavírus, posteriormente denominada COVID-19, é altamente transmissível e patogênica. Os sintomas mais comuns dessa doença são tosse seca, dor de garganta e febre. Os sintomas podem progredir para uma forma grave de pneumonia com complicações críticas, incluindo choque séptico, edema pulmonar, síndrome do desconforto respiratório agudo e falência de múltiplos órgãos. Um grande obstáculo no controle da propagação desta doença é a ineficiência e a escassez de exames médicos. Tem ocorrido esforços crescentes no desenvolvimento de métodos de deep learning (DL) para diagnosticar a COVID-19 com base em imagens de tomografia. Esses sistemas de diagnóstico auxiliados por computador podem ajudar na detecção precoce de anormalidades na COVID-19 e facilitar a monitoração da progressão da doença, potencialmente reduzindo as taxas de mortalidade. Neste estudo, comparamos as estruturas populares de extração de recursos baseados em deep learning para a classificação automática da COVID-19. Para obter um modo mais preciso, que é um componente essencial de aprendizado, foram escolhidos um conjunto de redes neurais convolucionais (CNN) para treinar o nosso modelo. O desempenho do método proposto foi validado por meio de um conjunto de dados da COVID-19 com imagens de tomografias computadorizadas (TC). Esse conjunto de dados está disponível ao público, no qual contém centenas de tomografias positivas para a doença. Os métodos DL foram executados e a CNN melhor classificada conseguiu alcançar ótimos resultados de diagnóstico da COVID-19.

PALAVRAS-CHAVE: Rede Neural Convolucional, Transfer learning, COVID-19, Tomografia, Conjunto de dados.

1 INTRODUCTION

Coronavirus disease (COVID-19), which since December 2019, when it emerged in Wuhan, Hubei, China, has been termed an infectious disease that has infected an abundant number of people worldwide and caused more than one million deaths in the year 2020. A major obstacle in controlling the spread of this disease is the inefficiency and scarcity of tests. Several studies (Bernheim et al., 2020) have shown that computed tomography (CT) shows radiological signs resulting from patients with COVID-19 and are promising to serve as a more efficient and accessible test due to the wide availability of CT devices that can generate results quickly. Also, to alleviate the burden of medical professionals reading CT scans, learning methods (Gozes et al., 2020) have been developed that can automatically interpret CT images and predict whether they are positive for COVID-19. While these works have shown promising results, they have two limitations. First, the computed tomography datasets used in these works are not public due to privacy concerns. Also, the lack of a set of open-source images makes research and development of more advanced Artificial Intelligence (AI) methods quite difficult for a more accurate test based on COVID-19 CT. Second, these works require a large collection of CT scans during model training to achieve performance that meets the clinical standard.

Currently, patients with COVID-19 are primarily diagnosed by reverse transcription polymerase chain reaction (RT-PCR) to detect SARS-CoV-2 nucleic acid. Recently, due to the limited supply of RT-PCR kits, some specialists have proposed the diagnosis of suspected cases using computed tomography (CT) of the lungs, which saves time instead of RT-PCR (Xinhua, 2020). Typical clinical symptoms, epidemiological history, and positive tomographic images are vital indicators for the detection of suspected patients. Identifying a large number of tomography images accurately, especially in the epidemic area, is a relevant topic at the moment. Deep learning (DL) has proven to be an effective tool to classify common signs of lung disease images in recent years. According to Sun (Sun, Zheng and Qian, 2016), he proposed an Lung Image Database Consortium (LIDC) database and tested some DL methods, including a Convolutional Neural Network (CNN), that is, a class of artificial neural network from feed-forward type, which has been included with relevance in the analysis and processing of digital images (Chityala and Pudipeddi, 2020). Meanwhile, Kang (Kang, Min and Ye, 2017) showed that CNN has improved on LIDC's rating problems. In addition to all this, DL has been widely used in automatic diagnosis (Peng, Xinnan and Hongwei, 2018), in the detection of pulmonary nodules (Li, 2017), and classification (Song, Zhao and Luo, 2017). Therefore, an improved CNN was used, in order to extract the evident characteristics and the internal representation of the image simultaneously, showing an excellent performance in the classification task of ImageNet (Deng, Dong and Socher, 2009), a large database designed for use in visual recognition.

Hemdan (Hemdan, Shouman and Karar, 2020) developed a deep learning framework, COVIDX-Net, to diagnose COVID-19 on X-ray images. A comparative study of different DL architectures, including VGG19, DenseNet201, ResNetV2, InceptionV3, InceptionResNetV2, Xception and MobileNetV2, is provided by the authors. The public dataset of X-ray images were provided by Dr. Joseph Cohen (Cohen, Morrison and Dao, 2020) and Dr. Adrian Rosebrock (Rosebrock, 2020). The dataset provided includes 50 X-ray images, divided into two classes into 25 normal cases and 25 positive COVID-19 images. Hemdan's results showed that the VGG19 and DenseNet201 models achieved the best performance scores among counterparties with 90% accuracy.

According to Hall (Hall et al., 2020), a VGG16 architecture was used and they made a transfer learning strategy with cross-validation 10 times trained in the dataset of Dr. Joseph Cohen (Cohen, Morrison and Dao, 2020). The general concept of the method is to use a pre-trained model in another set of data, usually larger, to solve a new problem. All images were resized to 224×224 pixels and a data addition strategy was employed to increase the size of the dataset. The proposed approach achieved an overall accuracy of 96.1% and an area under the curve (AUC) of 99.7% in the dataset provided.

The difference between CT images and X-ray images is that the former can detect details with much more precision and clarity. Thus, it is more recommended in cases where the doctor needs to assess the patient's symptoms with COVID-19 in more detail. However, the x-ray, although simpler, remains a fundamental exam to diagnose minor problems, without the need to use the latest equipment.

The main motivation of this study is the COVID-19 diagnosis challenge with CT images from Grand Challenge website (Grand Challenge, 2020). The idea is to present a generic method of resource extraction using convolutional neural networks that do not require manual or very complex resources of input data, is easily applied to different categories, such as CT images. Another main objective is to reduce the generalization error while obtaining a more accurate diagnosis. Contributions are summarized as follows:

• To overcome the problem of overfitting in deep learning due to the limited number of training images, a transfer learning strategy is adopted, since the training of very deep CNN models from scratch requires a large number of training data;

• The proposed approach dramatically reduces the detection time, achieving good results, which is a superior advantage for the development of real or near real-time inferences in medical applications.

The rest of this work was organized like this: the proposed methodology to automatically classify COVID-19 and normal cases are explained in Section 2, where the dataset, experimental settings, and performance metrics are also provided. The analysis of the results is mentioned in Section 3 and, finally, the conclusions are presented in Section 4.

2 METHODOLOGY

2.1 Dataset

In this article, the goal is to develop sample-efficient deep learning methods that can achieve an accurate diagnosis of COVID-19 with CT scans, even when the number of training images is limited. With this, a COVID19-CT dataset (Zhao et al., 2020) confirmed by a senior radiologist at Tongji Hospital, Wuhan, China, was used to diagnose and treat a large number of COVID-19 patients during the outbreak of this disease between months January and April. It contains 349 CT images with clinical findings from 216 cases of patients positive for COVID-19, and 397 CT images of 171 patients with lung cancer and normal cases, that is, negative for COVID-19. The images are collected from medRxiv and bioRxiv documents on COVID-19. Some low-quality images with text, letters, numbers, arrows or markings were manually discarded. Figure 1 shows some examples of computed tomography of positive and negative COVID-19 patients. For better understanding, it is the largest COVID-19 CT scan dataset today and all images are open to the public for research purposes.

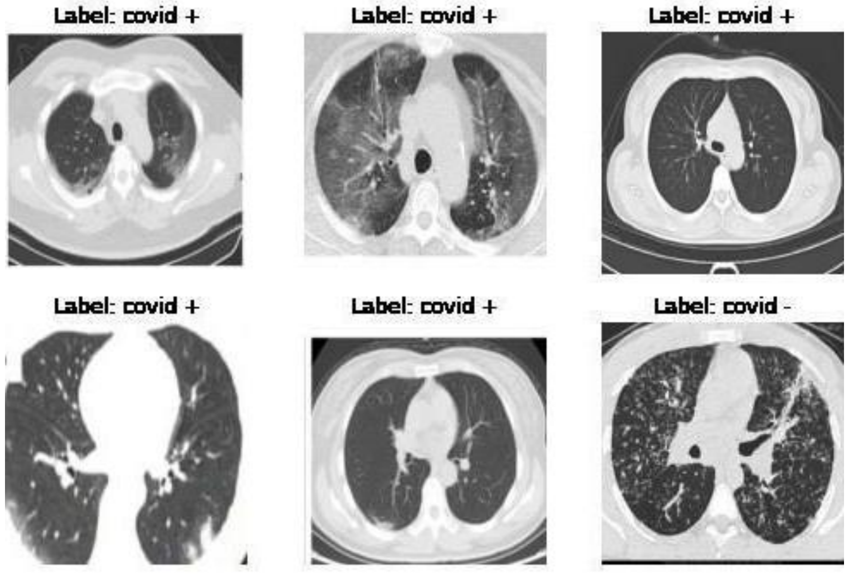

Figure 1: COVID-CT dataset [14].

2.2 Pre-processing details

The images in the dataset were collected at various imaging clinics with different equipment and image acquisition parameters. Therefore, there are considerable variations in the intensity of the images. The method proposed in this study avoids extensive pre-processing steps to improve the generalizability of the CNN architecture. This helps to make the model more robust to noise, artifacts, and variations in input images during the resource extraction phase.

In this dataset, images vary in resolution and size. Therefore, the input images were resized to 224×224 pixels, as needed for the VGG (Simonyan and Zisserman, 2014), DenseNet (Huang et al., 2017), MobileNet (Howard et al., 2017), ResNet (He et al., 2016), and NASNetMobile (Zoph et al., 2017) architectures, that is, they will be tested 11 networks for each training stage.

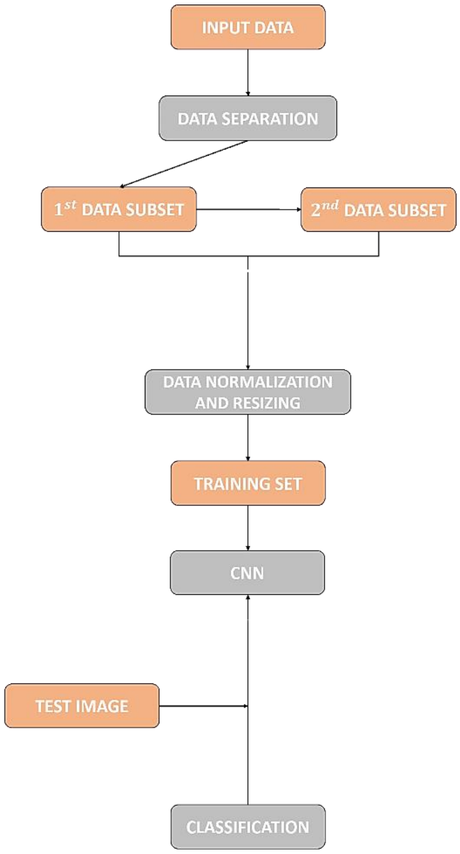

Figure 2: Workflow of the proposed methodology.

In Figure 2, the input data correspond to the dataset provided by the challenge, which was divided into two subsets, one with CT images of positive patients and the other with CT images of negative patients from COVID-19. From there, the two groups follow the scheme in parallel: the normalization process that changes the range of pixel intensity values and the resizing of the data that are applied to them and the different CNN models trained for each architecture, that is, 80% of the images are for training and 20% are for testing. And finally, we get the classification of the metrics.

2.3 Network training with transfer learning

Few studies have been published on the application of deep CNN descriptors on CT images. Each of CNN's architectures is built by different modules and layers of convolution that help to extract fundamental and important resources from a given input image.

The concept of transfer learning aims to leverage data-rich origin tasks to assist in learning a target task with data deficiency. Noting that, in this case, it is based on the diagnosis of the computed tomography of COVID-19. So the basic strategy is to learn a powerful extraction of visual resources, pre-training this network in large datasets in the source tasks, and then adapt this pre-trained network to the target task by adjusting the network weights in the set of small size data in the target task. Even with its overall effectiveness, transfer learning can be suboptimal because the initial data can have a large discrepancy with the final data in terms of the visual appearance of images and class labels, which makes the network resource extraction is influenced by input data and generalizes less well to output data (Jakubovitz, Rodrigues and Giryes, 2019).

Motivated by the success of deep learning models in computer vision, among the possible ways of using the knowledge or learning acquired by a pre-trained model for another application, the fine-tuning techniques (FT) stand out (Morocho-Cayamcela and Lim, 2019).

FT modifies the parameters of an existing CNN to train a new task. The output layer is extended with weights randomly started for the new task and a learning rate is used to adjust the parameters from their original values to minimize the loss. Fine-tuning requires updating the model architecture by removing the previous fully connected layer heads (FC), providing new and newly initialized heads, and training the new FC layers to predict our input classes (Shabbeer Basha, 2019).

First, we cut the final set of fully connected layers, that is, the “header” of the network where class label predictions are returned from a pre-trained CNN (Rosebrock, 2019). Then, we replaced the head with a new set of fully-connected layers with random starts. From there, all layers below the head are frozen so that their weights cannot be updated. We then train the network using a very small learning rate so that the new set of fully connected layers can learn patterns from the convolution layers previously learned on the network.

Then, we will initialize our selected models and configure them for fine-tuning, seen in Figure 3 (Yamashita et al., 2018) below.

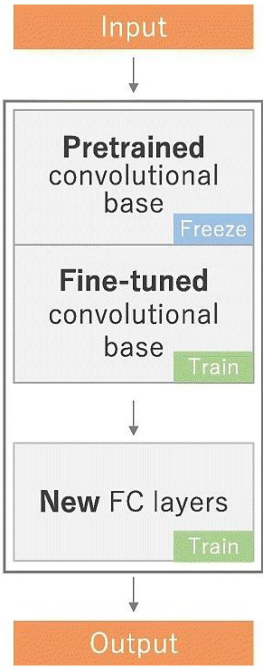

Figure 3: Fine-Tuning method.

The technique was adopted to evaluate the average performance of the generalization of the classifiers in each experiment. For all CNNs, the network weights were initialized from the weights trained on the database ImageNet (Krizhevsky, Sutskever and Hinton, 2012), being fundamental for the advancement of deep learning. Since the data is freely available to researchers for non-commercial use.

Based on the concept of Rosebrock (Rosebrock, 2020), to ensure the generalization of our model, we performed the data increase by setting the random rotation of the image at 15 degrees clockwise or counterclockwise. The models were also compiled with the help of the Adam optimizer, which updates the weights of the network based on the training data.

The compilation parameters were also inspired by Rosebrook, where there were 25 epochs and a value equal to 8 for the lot size (Rosebrock, 2020). Therefore, we evaluated the effectiveness of the transfer learning strategy with several network architectures and a pre-trained dataset.

The low-cost Linux-based computer system used for this experiment had an Intel (R) Core (TM) i5-7200U 2.50GHz processor with 4GB of RAM, that is, without a GPU (Graphic Processor Unit), being a microprocessor integrated with a computer specialized in processing graphics, used by the models of Hemdan (Hemdan, Shouman and Karar, 2020) and Hall (Hall et al., 2020). The training and testing process of the proposed architecture for this experiment was implemented in Python using the Keras package (Keras Team, 2018) with Tensorflow (Abadi et al., 2015) as the back end of the deep learning structure.

2.4 Challenge rules

To measure the performance of the prediction of the methods in this study, we used common evaluation metrics (Voigtman, 2017), such as recall, precision, accuracy, and the F1-score.

$$\text{Recall} = TP / (TP + FN) \qquad (1)$$

$$\text{Precision} = TP / (TP + FP) \qquad (2)$$

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN) \qquad (3)$$

$$\text{F1-score} = 2 \times (\text{Recall} \times \text{Accuracy}) / (\text{Recall} + \text{Accuracy}) \qquad (4)$$

According to the Grand Challenge, the result will be according to the best F1-score to classify the submissions together with the accuracy, which involves classes such as the false negative rate (FN) and the true negative rate (TN), and AUC (area under the curve) shows the false positive rate (FP) when it grows as the true positives rate (TP) when it increases.

3 RESULTS AND DISCUSSIONS

An analysis of the proposed networks was carried out to better understand how they were good in classifying the data. According to the rules of the challenge, the MobileNet model achieved the best performance among the 11 networks tested. It produced an F1-score of 95%, an accuracy of 93%, and AUC of 94% in the set of test images. Second, it was the DenseNet121 model with an F1-score of 92%, an accuracy of 89%, and AUC of 91%. Third, the MobileNetV2 model with an F1-score of 91%, an accuracy of 89%, and AUC also of 89%. The CNN that ended up having the worst performance was VGG19, that is, it produced an F1-score of 84%, an accuracy of 81%, and AUC of 76%. The results obtained are shown in Table 1 below for better visualization.

Table 1: Classification of the metrics of the CNNs tested.

CNN	Accuracy	F1-score	AUC
MobileNet	**0.93**	**0.95**	**0.94**
DenseNet121	0.89	0.92	0.91
MobileNetV2	0.89	0.91	0.89
ResNet50	0.88	0.90	0.87
ResNet101	0.86	0.90	0.85
DenseNet169	0.86	0.88	0.85
ResNet152	0.85	0.88	0.85
NASNetMobile	0.84	0.88	0.82
DenseNet201	0.83	0.87	0.79
VGG16	0.83	0.87	0.79
VGG19	0.81	0.84	0.76

In the midst of these metrics obtained, it is also worth mentioning that the MobileNet model achieved an accuracy value of 98% and recall of 96%. Details of the training and testing of the dataset are visible in figures 4 and 5 below.

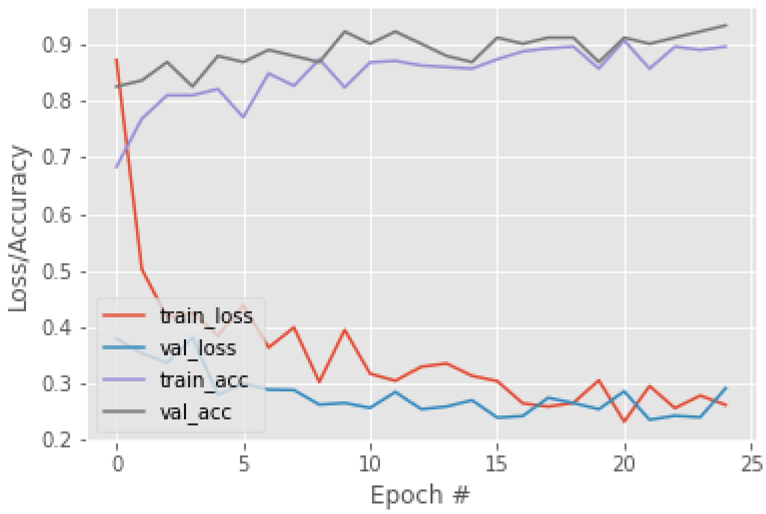

Figure 4: Training the dataset using MobileNet.

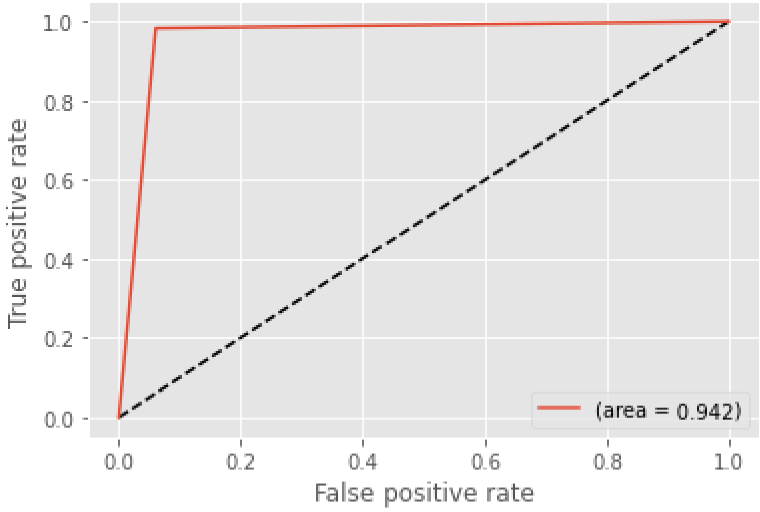

Figure 5: ROC curve.

The results achieved may resemble a young radiologist with a relatively light medical work situation. However, compared to a radiologist who needs around 30 minutes to diagnose a computed tomography (Cowan, MacDonald and Floyd, 2013), the MobileNet model already trained may take a few seconds to give the final result.

There are some limitations to the experiment performed. First, it is a pilot study on the application of deep learning in a new emerging pneumonia detection with a limited number of images of patients with COVID-19. Second, the impact of differences in tomography equipment is not currently considered. Therefore, recent research needs to include data from different sources to verify whether the effectiveness of a model trained in the detection of COVID-19 in CT scans is widespread.

4 CONCLUSIONS

The ongoing pandemic of COVID-19 has been declared a global health emergency due to the relatively high infection rate of the disease. At the time of writing, there were no clinically approved drugs or therapeutic vaccines available to treat COVID-19. Early detection of COVID-19 is important to interrupt community transmission of the disease and patient care. Currently, isolating and quarantining suspected patients is the most effective way to prevent the spread of COVID-19. Diagnostic methods, such as tomographic images, are playing an important role in monitoring the progression and severity of the disease in patients positive for COVID-19. Therefore, this article presents a classification approach for deep learning and machine learning based on extraction for the computer-aided diagnosis of COVID-19 pneumonia.

In this article, we study how to develop DL methods to accurately diagnose COVID-19 from computed tomography (CT) scans. Through transfer learning, it is possible to accelerate and improve a deep model with ease, in addition to also reducing the computational costs linked to training. After completing the processes, we demonstrate the effectiveness of our methods. Therefore, the experimental results in the available CT dataset demonstrate that the resources extracted by the MobileNet model generated a very accurate 95% forecast in terms of F1-score. At the time of writing, the model was in 5th place in the Grand Challenge partial ranking.

Thus, it is believed that the idea contributes in a relevant way to society, providing support for researchers in the areas of computer vision and health, as a source of consultation for methods of reducing the mortality rate from heart and respiratory diseases. It is also possible to notice the little processing required to execute such techniques and their low cost, guaranteeing the fact that it is a very promising area.

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