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Deep learning based computed tomography image classification of COVID-19 patients

A. Seethalakshmy *
Department of Mathematics
Saveetha School of Engineering
Saveetha Institute of Medical and Technical Sciences
Chennai
India

T. Tamilvizhi †
Department of Computer Science and Engineering
Panimalar Engineering College
Chennai
India

K. Naga Sowjanya §
Department of Information Technology
Vel Tech Multi Tech Dr. Rangarajan Dr. Sakunthala Engineering College
Chennai
India

Bhoomeshwar Bala ‡
Department of Computer Science
Debre Tabor University
Debra Tabor
Ethiopia

Abstract

Accurate identification of the newest 2019 coronavirus (COVID-19) disease is required for effective illness behavior and management. To categorize and analyses COVID-19 in the prevalent region, for (COVID-19) detection using medical images, computed tomography

* *E-mail:* **apseethalakshmy@gmail.com (Corresponding Author)**
† *E-mail:* **tamilvizhi.phd.it@gmail.com**
§ *E-mail:* **sowjanyakasi1@gmail.com**
‡ *E-mail:* **drbhoom08@dtu.edu.et**

(CT) imaging is informative, reliable, and quick. Chest CT images are readily available in nearly all hospitals, making it possible to use them to classify COVID-19 patients early on. When COVID-19 infection spreads quickly, a significant amount of time are required for the chest CT-based COVID-19 categorization. Since medical practitioners have scarce time, a computerized analysis of CT scans is required. In this paper, we construct a classification framework involving the extraction of CT image characteristics and categorization. The framework is separated into training and testing modules, with training the classifier aiding in the development of a model that efficiently classifies CT images as input. Deep convolutional neural network including VGG16, ResNet50, DensNet121, and inspectionResNetV2, variations were utilized as classifiers in the present investigation (DCNN) different machine learning and Statistical modeling techniques to identify COVID-19 infections probability and discover lesion for training.

Subject Classification: *Primary 93A30, Secondary 49K15.*

Keywords: *Convolutional neural network, CT image classification, Deep learning, Transfer learning.*

1. Introduction

Rapid diagnosis and treatment are key for stopping the spread of COVID-19 and managing its symptoms. The most common preliminary test for detecting it is RT-PCR testing. It is possible to get detailed organ, soft tissue, bone, and blood vessel images via X-rays or a computed tomography (CT) scan. When it comes to identifying inner structures, there are a range of CT imaging techniques available. Conventional radiographs produce several images of the same part of the body, but CT scans produce only one slice of the same area of the body, with no overlap between the different bodily features. When compared to standard X-rays, CT scans provide a significantly more accurate image of a patient health condition. It is possible to use this information for the determination of medical condition present and the location and extent of the problem. As a result of this rationale, many machine or deep learning moles are used for finding the problem while screening the lungs using CT scans for use in CT scans.

A more compact baseline model also makes it possible to employ inputs with better resolution without incurring excessively high computing costs, as opposed to a more complex baseline model. As a general rule, the cost of computing resources has a considerable impact on how widely a technology is offered. In this work, we introduce a feature extraction and categorization technique for CT scans. In this study, deep convolution neural networks (DCNNs) of several types are used. Modules for training and testing are divided into the framework, and in each module, the classifier is taught to generate a model that accurately classifies the CT images that are fed into it.

2. Previous work

Various models on deep learning have achieved breakthrough performance, which has been made possible by annotated massive datasets. Deep learning approaches are particularly effective in various applications of image processing. In current years, the practice of deep learning on Chest CT scans and X-ray for the detection of various lung illnesses has grown in popularity, particularly for the detection of lung cancer. Machine learning models have been used to investigate CT-based diagnosis for COVID-19, which have been the topic of various investigations. The following are a few representative studies that have been summarized and explored in more detail below. Harmon et al. [1] employed a diverse population to train and test a number of deep learning networks in order to find lung parenchyma and identify covid to diagnose COVID-19 pneumonia.

Using an average of scores from different lung locations, researchers obtain a specificity of 90.1%. According to Wang et al. [2], a programmed identification using deep regression outline for pneumonia is done by considering the CT scan images as input and then clinical data has been created. As illustrated in this paper, a ResNet50 extracts well the visual information using the ResNet50 network. An LSTM network was used to analyze the clinical information acquired from patients and concatenate it with demographic features (age and gender) and CT scans. A massive dataset was used by Kingsley et al. [3] to develop an artificial intelligence system that used chest CT features along with scientific data in order to differentiate COVID-19 individuals. On other hand, a senior radiologist used the combined model and attained a 93.8% specificity. There are several disadvantages to using various systems. This is especially true when there are a large number of suspected patients who are awaiting diagnosis.

In a recent study, Zhou et al. [4] advocated that chest CT scans be used to spot COVID-19 impurity regions. This is accomplished by the use of two-dimensional U-Nets. The sum of the three intermediate binary predictions is used to detect infected pixels, with a threshold value of two being used to identify them. After including the upgraded data, the proposed approach attained a sensitivity of 77.6% and an improved sensitivity of 78.3%. During this pandemic, it will be difficult to collect enough high-quality annotations to allow deep learning to be used to automate the lesion identification process. Learning using noisy labels to generate and helps to lessen this difficulty in learning. A new framework for machine learning was established by Wang et al. [5] by employing noisy COVID-19 infection masks. The researchers initially developed a dice loss integrating the mean absolute error and dice loss, which they called the dice loss metre (MAE). Following this, the creation of a pneumonia lesion segmentation was undertaken, which is capable of distinguishing between COVID-19-infected regions of varied sizes and shapes.

Wang et al. [6] developed a deep controlled learning approach for infection location determination. Because there is no specific segmentation model for infection localization in the approach, ground-truth masks by a radiologist to evaluate network performance rather than annotations during the training phase of the proposed technique. According to the authors of [7], DRUNET was utilized to conduct lung and lesion segmentation in computed tomography images, with a DSC value of 95.9% for lung division. When it comes to lesion segmentation, a DeepLabv3-based network achieved a mean DCS (DSC) of 58.7%. When it came to lung and lesion segmentation, the network was trained on 4695 CT slices. Because just 201 scans were used in the published results, the authors of found that they needed a large annotated dataset to work with. This is a concern that has been mentioned previously in published research. Because the authors of worked with images in a 3D environment, their computations were more expensive and their analyses took longer to complete than those of other authors.

To better understand the abnormal CT patterns, Chaganti et al. [8] created a technique for segmenting and calculating CT patterns. Chest CT scans from 9749 patients helped researchers create 97 severity matrices, which included the following measures: opacity, pulmonary severity score, etc. These matrices were then used to create a final severity score, which was based on the data. Despite the fact that the models worked admirably, there was no clear evaluation measure for them to follow. The UNET model was utilized for lung and lesion segmentation, and the median DSC for both models was 0.85%, according to the results. A patients are evaluated using a system that integrates both computer and radiological evaluations for the determination of severity in lung. To segment the lesion, adaptive region growth and thresholds were used in conjunction with thresholds. Small sample numbers may lead to a biased decision of computer-based methodologies. In the automated system established by Tamilvizhi et al. [9], 120 patients to evaluate the U-Net for vascular and lung segmentation.

The representations were trained and evaluated consuming data from the patients. The proposed approach was successful in separating the lungs from the lesions in 95% and 81% of the cases, respectively. Despite the fact that the huge majority of the evaluated studies provided positive findings for lung and infection segmentation in the majority of cases, they relied on conventional U-Net architectures and other image processing techniques [10]. The feature pyramid network (FPN), among other encoder–decoder (E-D) CNNs, has been shown to deliver optimal segmentation. It is necessary to study the capabilities of lung detection architectures and localization of infection [11, 12].

3. Proposed Method

The proposed CT screening strategy for COVID-19 is achieving the Mobile Net was expanded and trained using CT scans of healthy and SaR-CoV-2-infected patients in order to improve its concert. The data sets provided in the preceding section was utilized to generate CT images, which were then subjected to pre-processing. Pre-processing techniques are fairly popular in computer vision applications, and they are used in a variety of ways. Some pre-processing techniques can assist in the removal of unwanted noise, the identification of sections of an image that can be used to aid in the gratitude task, and even the training phase of deep learning algorithms .In this scenario, the only thing that has to be done is to normalize the pixel intensity between [0] - [1]. This pre-processing step is necessary in order for the model to come together appropriately during training. In CNNs, the images are routinely scaled in order to guarantee that the network design is compatible with the network architecture. MobileNetv2 has a lesser cost in terms of computation with reduced memory use and latency that makes it ideal for making use of higher definition images. We also investigate whether altering the input resolution has an impact on the model quality, which we do as well. A new parameter is added to the network as a result of this pre-processing step being added to it.

Starting with the CT slice provided as input, a MobileNetv2 model is used to create a mask based on the information in the slice. Using the segmented input, a second deep learning model is trained to find infection in CT. The infection mask that has been produced will be used to detect COVID slices. COVID-19 infections and lung parenchyma are segmented from the input CT slices via mobilenetv2 lightweight model, which was developed by the National Institutes of Health. When it comes to MobileNetV2, there are two types of blocks. Stride 1 is only found on one of the two remaining blocks, which is the last one. Another option for condensing is to use a block with a stride length of two. Both types of blocks are made up of three layers. This time, the first is a 1x1 convolution with ReLU6 as the input signal. A depth-wise convolution is used in the second layer. Layer three is a 1x1-way convolution, but this time there is no non-linearity in the results. Deep networks, according to some, only have the power of linear classifiers on non-zero volume regions of the output domain if RELU is applied once more in the training process.

The context of the contracting path is acquired by MobileNetv2 powerful segmentation algorithm, which allows the expanding path to pinpoint its location with pinpoint accuracy. It is a convolutional neural network architecture that been optimized for mobile devices like smart phones and tablets. Because the bottleneck layers are joined by an inverted residual structure, this approach works well. Non-linearity is introduced into the model at the intermediate expansion layer by the use of lightweight depth wise convolutions, which are applied at the intermediate expansion layer. The overall design of MobileNetV2 begins with a convolution layer that contains 32 filters and is followed by 19 bottleneck layers. Except for the first layer, the network expansion rate remains constant. Expanding networks at a rate between 5 and 10 times the rate of growth results in nearly equal performance curves, with smaller networks benefiting from slower growth and larger networks benefiting from faster growth, respectively. Data augmentation increases the training samples by modifying images without removing their semantic value, which is known as image transformation. In this work, the training samples were rotated, horizontally flipped, and scaled in order to improve their accuracy. There are only a few images of the COVID-19 class available for use in this work because there are so few of them. It is impossible to exaggerate the significance of transfer learning. We derive a large number of our models from Mobile Net, and the additional layers are all initialized with a mean of zero. When Mobile Nets were first trained on the Image net dataset, they were called mobile networks. As a result, in order to transfer knowledge between domains, we go through the following procedures:

Step 1. Create a new Mobile Net model and copy the weights from an existing one to use as a starting point.

Step 2. Modify the model architecture by adding additional layers;

Step 3. Randomize the initialization of the new layers.

Step 4. After determining which levels will be subject to the learning process and which layers will remain static in Step 4, it is time to determine which layers will be subject to the learning process.

Step 5. The weights are updated in accordance with the loss function and optimization process that were used.

The Adam Optimizer is employed to maintain the weights up to date because of its high learning rate (10–4). Our aim is for the learning rate to reduce by a factor of ten in the event that we reach a standstill. The number of epochs is limited to ten.

3. Results and Discussions

Go over the two sets of data that we used to conduct our investigation in this part. According to our understanding, these are the two largest publicly available datasets that have ever been made available. CT-scan dataset is presented and asks for randomly partitioning the dataset into training and testing for evaluating approaches. The dataset is available at https://www.kaggle.com/plameneduardo/sarscov2-ctscan-dataset. The photos in this collection are CT scans, although there is no image size requirement. COVID-CT dataset Patients infected with COVID-19 were screened with CT pictures, some of which were collected from scholarly articles and repositories, and some imaging images were donated.PDF was used to extract the images from the texts while maintaining the high quality of the images. Patient information including such as gender, age, medical history, location, severity, scan time, and medical report were all carefully retrieved and connected with each image in a meticulously organized manner. A total of 463 images were taken of the 55 patients who were investigated. The CT dataset has a specified requirement for contrast and size, which is similar to the prior dataset. The validation and testing sets were constructed using images collected and images directly acquired from medical equipment. Table 1 contains a summary of the datasets that have been presented here. There are faults in the datasets that may be seen in the table, along with the number of patients in each patient classes.

Table I

Distribution of datasets

Dataset	COVID-19		Non-COVID-19	
	Number of Patients	Number of Images	Number of Patients	Number of Images
CT-scan dataset	60	1252	60	1230
COVID-CT	216	349	55	463

The training and testing sets are divided at random from one another. When doing the slice evaluation, all CT scans are reviewed individually, but the patient division is taken into consideration, so that samples from similar patients are not used in training and testing. As a result in Fig.1, the model will always be tested on samples taken from unidentifiable people. Evaluation is used to arrive at an individual diagnosis rather than an image-by-image diagnosis after all images of an individual have been evaluated. In some cases, an evaluation that takes into account all conceivable scenarios involving a single individual may increase the likelihood of a positive rates.

The accuracy of lesion classification is demonstrated using CT lung images. The detection of positive cases is considered critical, and hence the accuracy is the most important characteristic in our analysis. The best result (99.64% accuracy) was obtained by using MobileNetv2 networks as the backbone, demonstrating that the proposed approach achieves a high robustness. Even more impressive is the fact that using Mobile Net as the backbone prevented 98.72% of false positives from being generated. As can be observed, when comparing the model performance across datasets

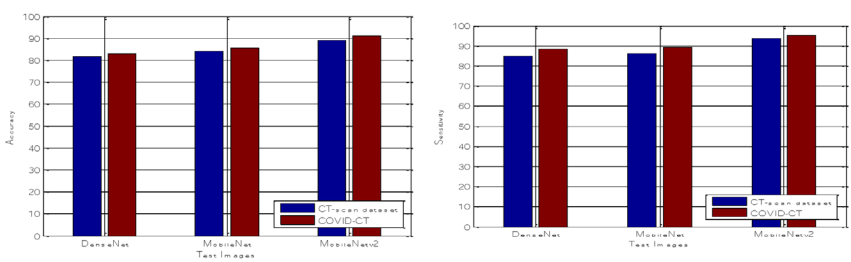

Figure 1

(a) Accuracy of CT-scan dataset and COVID-CT (b) Sensitivity of CT-scan dataset and COVID-CT

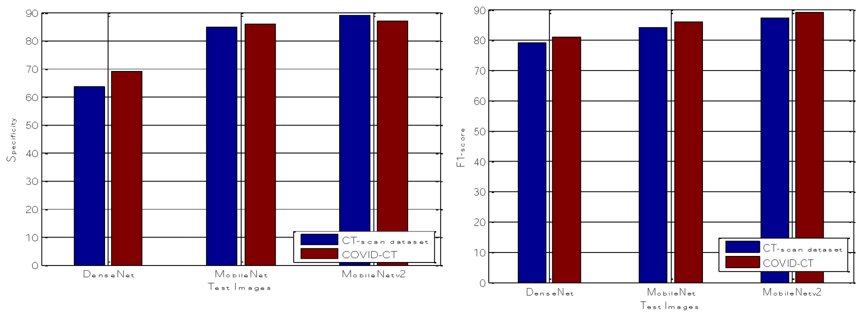

Figure 2

(a) Specificity of CT-scan dataset and COVID-CT b) F1-Measure of (a) CT-scan dataset (b) COVID-CT

to its performance inside datasets, this model performance is significantly reduced. Images from datasets is obtained via various equipment, and as a result, the fundamental characteristics of the images can be changed, making identification more difficult. As evidenced by this, MobileNetv2 segmentation is really close to the truth as in Figure 2. It is intriguing to see how well the three networks perform when it comes to creating a segmentation mask. This was transmitted to the deep learners in order to evaluate the network capacity to construct a mask for lung slices. Despite the fact that COVID-19 lesions can cause considerable damage to the lungs, the trained model was able to segment the lung borders with high accuracy. This demonstrates the resilience of the lung segmentation model developed in this research.

4. Conclusions

In this research, the suitability of deep learning for COVID-19 diagnosis using medical imaging. without the need for annotating the COVID-19 lesions in CT volumes for training, our weakly –supervised deep learning framework obtained strong COVID-19 classification performance and good lesion localizations results. Therefore, our algorithm has great potential to be applied in clinical application for accurate and rapid COVID-19 diagnosis, it is advantageous to detect both false positives and false negatives, since this would improve accuracy.

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