COVID -19 Detection based on CT Scan Images using Deep Learning Methods

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Abstract. Since the outbreak of COVID-19, there are many attempts to investigate techniques to detect COVID-19 cases using a quick and safe procedure. Utilizing radiology modality to identify the existence of COVID-19 was considered the prominent method for COVID-19 screening. CT scans play an important role as the novel modality for COVID-19 detection. In this paper, we study the current advanced in COVID-19 detection using CT Scan images and deep learning. In this survey paper, three state-of-the-art methods are analyzed including TeliNet, CovidCTNet, and Covid DeteCT, then we describe the advantage and disadvantages of each method and analyze the performance of these methods. We also discuss the limitations and future directions to enhance the performance of these approaches.

Keywords: Coronavirus, COVID-19, Radiology images, CT Scan

1 Introduction

The standard testing method for COVID-19 is RT-PCR, which is one variation of PCR testing that adds one step of RNA to DNA reverse transcription. The benefit of RT-PCR is its high sensitivity, reliability, and real-time. However, it still has some drawbacks, such as false-negative rates are high, giving us only the presence of the virus but not the real infected detection, and the cost to establish the laboratory and trained technicians. Meanwhile, using radiology methods to detect COVID-19 can replace RT-PCR as the prominent alternative for many reasons. First, using the radiology method, especially, CT Scan reduces the large cost to set up the facility for testing. Second, the procedure is simple, no need to take the sample, which reduces the possibility of spreading the virus. And lastly, the method is reliable and real-time since the available CT Scan images for training and the inference time of the method is just a few seconds.

2 Related Works

There are many attempts to apply deep learning and radiology for COVID-19 detection. We can name some of them, such as the work of Horry, Michael J., et al [1] which try

to detect COVID-19 using multimodal radiology images and transfer learning. Another work by Amyar, Amine, et al. [2] proposed multi-task deep learning to classify and segment COVID-19 pneumonia based on CT Scan images. In the work of Polsinelli, M, et al. [3] the authors try to enhance the performance of Convolutional Neural Network (CNN) architecture by using a lightweight CNN which is 10 times faster and better than complex CNN. CNR-IEMN is a multi-task and multi-stage deep learning approach that use XG-Boost classifier in the second stage.

3 Methodology

In this study, we analyze three convolutional neural networks, which are TeliNet, CovidCTNet, and Covid DeteCT. The reason that the author had chosen these neural nets is because of the simplicity, robustness, and efficient performance of this network when running on the medical dataset, especially on Chest CT Scan images.

3.1 TeliNet

A simple and efficient Convolutional Neural Network dedicated to CT images to diagnose COVID-19 associated with ICCV 2021 competition [4]. The network's main idea is to try to minimize layers of the architecture to cut down the number of parameters in the network overall.

Network Architecture. The shallow network consists of four layers, including 2D convolutions, max pooling, LeakyReLU, and batch normalization layers. The total number of trainable parameters is no more than 8.5 million and 15 times lighter than the well-known VGG-16 [5] which contains over 134 million parameters. The input image size is 256 x 256, the convolutional layers use 16 filters of size 3x3, follow are LeakyReLU [6] activation functions and max pooling. After the convolution layers are two dense layers and finally is the Sigmoid for binary classification.

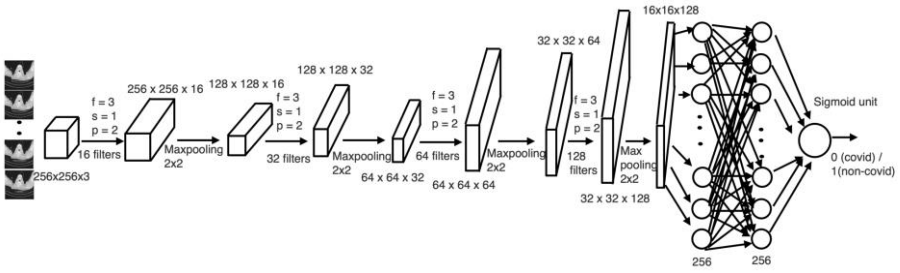

Fig. 1. TeliNet Architecture Overview.

Dataset. The dataset was downloaded from MIA-COVID which contains 609057 chests of CT scan images and divided into two COVID-19 and nonCOVID-19

categories. There is a total of 5000 CT scan series divided into three subsets, the training, validation, and test set.

Results. On F1 macro score, the TeliNet (0.81) outperform VGG-16 (0.72) and compares to the standard benchmark (0.7). The experiment was conducted on MacBook Pro with 8 GB of ram. The experiment tries a range of batch sizes from 4 to 128 and picks up the best result of 32.

Table 1. TeliNet F1 score result.

Method	Train
TeliNet	**0.81**
VGG-16	0.72
Benchmark	0.7

3.2 CovidCTNet

This open-source project contains algorithms and a CT scan dataset for COVID-19 detection purposes. The method aid doctor with screening and detecting COVID-19 and the open-source code is freely distributed and modified for future advancement.

Network Architecture. The architecture used in CovidCTNet [7] is BCDU-Net which plays an important role when dealing with a small dataset, especially tasks in the medical domain. The overall architecture uses multistep to train and detect COVID-19. The first step in the training pipeline is to train a subset of the dataset, then the second step is to feed all the datasets to the trained model from the first step, then the last step is to classify the CT scan images by using a customized convolutional neural network.

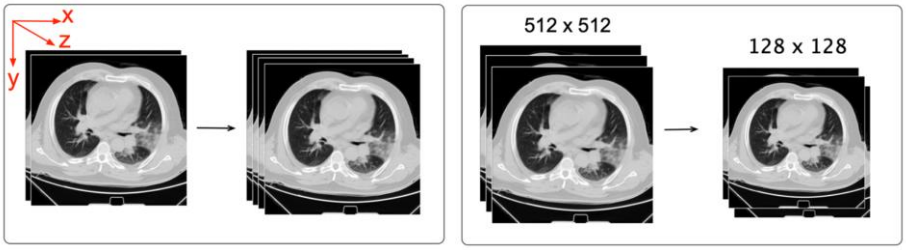

Fig. 2. Preprocessing phase in CovidCTNet training pipeline.

Dataset. The dataset was acquired from 335 patients, with a total of 16750 slices, and the second dataset of 115 patients with 5750 slices. In addition, the dataset from lung nodule classification was added to the training dataset with 70 CT scans. Overall, the dataset contains images from different institutions and countries.

Results. The CovidCTNet boosted the accuracy of COVID-19 detection with 93% of sensitivity and 95% of accuracy. Compare to other state-of-the-art methods, CovidCT-Net outperforms these approaches on AUC, Sensitivity, and Specificity matrices. Besides optimizing and improving detection accuracy, CovidCTNet plays an important role in clinical treatment with simple and cost-effective methods.

3.3 Covid DeteCT

The author of Covid DeteCT [8] proposes a novel method that classifies and detects COVID-19 cases based on the entire volume of chest CT scan images. The training pipeline uses a multi-center dataset across 8 countries to train and test the neural network architecture and output reliable and accurate results for COVID-19 detection.

Network Architecture. The proposed method Deep COVID DeteCT short for DCD is a customize convolutional neural network with 27 feature extractor layers and 1 fully connected layer. The architecture uses cross-entropy as a loss function and Adam as an optimization method with 20 epochs of training in total. DCD used Inception3D as the backbone of the model and the training pipeline contains 2 tasks. The first task is the classification task, the author uses a hold-out external test set, and the validation set uses an internal dataset. And the task was evaluated based on the Area under Curve (AUC) [9] and Receiver Operating Characteristics (ROC) [10]. The second task is the prognosis task to predict clinical features such as length of hospital stay.

Dataset. In this paper, the author uses the RICORD COVID-19 dataset, which is a freely distributed multi-institute and multi-nation dataset and was labeled by an expert. The dataset contains 240 CT scan slices, and the pathway of dataset collection goes through five steps. First, the data aggregation must be shared agreement between patients and the institution, next step is deidentification using the RSNA toolkit. The third step is data transfer which transfers deidentification data to RSNA. Then radiologists join the team to annotate and segment the dataset. The final step is user access, which needs to have a user data agreement and download from the homepage site.

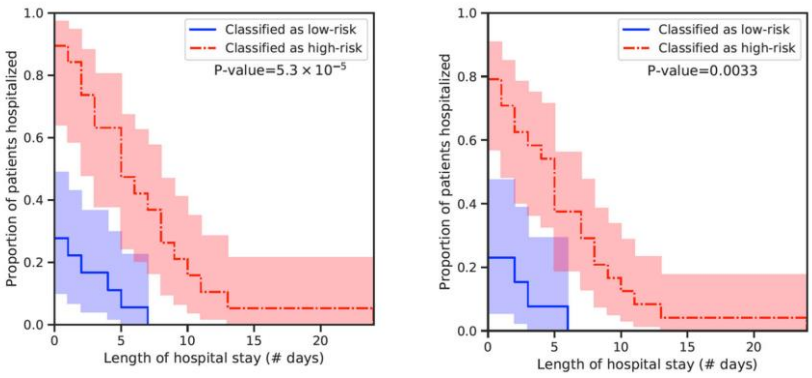

Fig. 3. Length of hospital stay prediction on the second task of DCD.

Results. In the classification task, the method outperforms ResNet-50 when training on 2D CT scan images. The DCD performance was also tested on a range of variations such as the soft tissue, the bone, and the lung with AUC above 0.8 in every test site. In the second task to predict the prognosis feature, DCD also provides us detail and precise prediction of features like the length of hospitalization and the follow-up patent over time.

4 Conclusion

In this paper, we study the application of deep learning for COVID-19 detection based on CT scan images. Three methods are subject to our investigation including TeliNet, CovidCTNet, and Covid DeteCT. These methods show that applying deep learning for CT scan image help to aid COVID-19 detection with high accuracy and reliability, in addition, radiology methods are efficient in term of cost and initial investment to build up testing facilities compare to the RT-PCR method. In future work, we will take the advantage of each method and then develop our algorithm to create a new tier of the network that is both lightweight, high accuracy, and easy to train.

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[Remarks]
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