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Application and development direction of deep learning in COVID-19 identification based on Computed Tomography images

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Abstract. Caused by the novel coronavirus SARS-CoV-2, COVID-19 is highly contagious via respiratory droplets from sneezing, coughing, or talking, and it can lead to severe respiratory issues, organ failure, and death. Early detection, treatment, and isolation of those at risk help slow its spread, it has challenged traditional diagnostic methods like RT-PCR due to limitations in sensitivity. CT imaging, aided by deep learning models, offers advantages in the early detection of lung abnormalities. This paper reviews the use of deep learning in analyzing CT images for COVID-19 diagnosis, highlighting advancements like image segmentation with U-Net and FPN, it also tracks the evolution of deep learning models in this domain, starting from initial applications focused on image classification and recognition to later advancements incorporating techniques like U-Net for image segmentation and feature pyramid networks. Novel techniques like multi-task learning and quantitative analysis show promise in improving accuracy. Future research focuses on enhancing training datasets, refining model architectures, and integrating methods to support clinical decision-making for COVID-19 management.

Keywords: COVID-19, Computed Tomography (CT) Imaging, Deep Learning, Image Segmentation, Computer-Aided Diagnosis.

1. Introduction

COVID-19, caused by the novel coronavirus SARS-CoV-2, is highly contagious via respiratory droplets from sneezing, coughing, or talking. It can lead to severe respiratory issues, organ failure, and death. Early detection, treatment, and isolating those at risk help slow its spread [1-3]. By January 13, 2023, there have been over 671 million reported cases of COVID-19 globally, resulting in more than 6.71 million deaths [4]. Two of the most effective methods for detecting COVID-19 are real-time reverse transcription polymerase chain reaction (RT-PCR) and chest radiology images, such as computed tomography (CT) and X-ray images. Due to the low sensitivity of RT-PCR, which is only 60%-70% and takes a long time, it is easy to produce many false negative results [5]. Therefore, computed tomography (CT) and radiography have played an integral role in the initial identification and diagnosis of COVID-19. CT imaging offers several benefits, including rapid visualization of lung issues, high sensitivity for early disease detection, and the ability to monitor disease progression. In cases related to SARS-CoV-2, CT scans can promptly reveal lung abnormalities in the initial disease stages, especially when RT-PCR tests yield false negative results [6]. However, due to the sheer volume of patients and the relatively small number of radiologists, accurately interpreting chest radiographs for each patient becomes challenging, leading to a higher rate of false positives [7]. To improve the situation, hospitals need computer-assisted lung CT diagnostic systems utilizing artificial intelligence (AI) and deep learning to accurately confirm suspected cases, screen patients and conduct virus surveillance, speed up the diagnostic process and prevent further spread of the disease.

With the rapid development of artificial intelligence, computer vision technology has evolved from initially classifying general images to being applied in medical imaging, including CT images [8]. In recent years, researchers have been dedicated to utilizing various artificial intelligence techniques, including machine learning (ML) and deep learning (DL) methods, for extracting information from CT images and diagnosing diseases [6].

The main issue of this paper is the application of deep learning in the identification of COVID-19 in CT images. By analyzing the work of different teams, the future development trend is found out, so as to provide the development direction and theoretical basis for the following research teams.

2. Overview form the perspective of Database

As the starting point of the COVID-19 outbreak, Wuhan and its surrounding areas in China had a large number of CT image samples at the early stage of the epidemic, especially the Wuhan Huoshenshan Hospital, which was built specifically to fight COVID-19. Zhang Haitao and his team used data provided by Huoshenshan Hospital to conduct their study [9]. However, the globalization of the data has been hampered by the highly contagious nature of the disease, making it difficult for regions outside China to use this precious and vast amount of data to train models. This led some of the team to choose to use another mainstream database: the Italian Society of Medical and Interventional Radiology (SIRM) public database. As a relatively complete public database in the early and middle period of the epidemic, many studies were carried out based on this data [10-12]. With the recommendation of time, more public databases of CT images on COVID-19 emerged, such as Covid-chest x-ray-dataset, COVID-CT, SARS-COV-2 Ct-Scan Dataset, etc.[13]. Research teams in different places and university-affiliated hospitals have also collaborated to build deep-learning databases by using data provided by hospitals [9,13-20]. Some teams also choose to use the stable database established by other teams and modify it to meet the team's goals for model training [21-22].

Due to the difficulty of data collection in the early days of the epidemic and the particularity of medical images, there were many problems with the database used in the study at that time. There was too little data, a large number of invalid images, and not enough radiologists to label the CT images used for training. These problems will lead to a decline in the accuracy of the model and a wrong judgment of the patient's condition, which is not conducive to assisting doctors in diagnosis and follow-up treatment. To solve the above data problems, different research teams have used different methods. In order to reduce the overfitting of the training image data, one team performed image enhancement on the data. The number of different images is increased using scaling, rotating, increasing Gaussian noise, adding blur, changing brightness and contrast, etc. [10,12,15]. Other teams are working on how to perform weakly supervised training on CT images [12,14,16,20,23-24], so that data can be used in deep learning without being labeled by radiologists, reducing data requirements.Over time, the research team tried to improve the accuracy of the deep learning model by increasing the amount of data and increasing the types of data to solve the generalization and overfitting problems of the model. They expanded the dataset beyond the typical normal and abnormal categories (COVID-19 patients) to include datasets representing a variety of pathological conditions [10,12,13,15-16,19-20,23]. These methods effectively extend training datasets to help deep learning models improve performance while assisting healthcare professionals in making more informed diagnostic decisions.

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3. Overview form the perspective of models

3.1. Early applications of deep learning

At different times, the research team chose different methods to train the model depending on the situation at the time. In the early days of the epidemic, due to the lack of CT image data and time constraints, the research team achieved its goal by training a deep learning model to classify the images and then identify them. The advantage of this is that the training cost is reduced and the model can be trained in a short time. The disadvantages are also obvious. The accuracy of the model is low, and using the same database for training and testing will lead to insufficient generalization and overfitting of the model [10]. Still, the research team is working to achieve its goal in other ways.

Hammam Alshazly and his team compared different deep-learning models to find the best one for detecting COVID-19 CT images [15]. After training different convolutional neural networks (CNN): SqueezeNet, Inception, ResNet, etc. and their variants, using the same data set, ResNet101 was found to be one of the best performing models available. The research team calculated a ResNet101 average accuracy and f1 score of 99.4%, achieving an average sensitivity of 99.1% [15]. Ali Abbasian Ardakani and his team also demonstrated that ResNet101 was a suitable model by comparing models. Compared with other models, it has higher image classification performance and the highest sensitivity, which is suitable for checking whether patients have diseases with higher sensitivity, such as COVID-19 [19]. ResNet101 uses residual learning that is easier to optimize than other structures, and its accuracy increases with depth [22].

3.2. Follow-up development

3.2.1. U-Net. Over time, there has been increasing concern about the accuracy of disease assessment models. At this point, the research team added an image cutting step on the basis of the previous training of the deep learning model for image classification and recognition, which is used to remove the useless part of the image and enhance the effective value of the data. The use of deep learning to complete image cutting is very conducive to saving unnecessary labor costs, and can derive more powerful functions, such as extracting the main lesion area while identifying, and better assisting doctors in diagnosis. At present, there are many methods to achieve image cutting, and the most popular one is using U-Net deep learning structure [11,14,18,23-24]. U-Net is a deep learning architecture for image semantic segmentation, which is unique in the combination of encoder and decoder. Skip links are used to effectively combine context and location information [25]. This design makes U-Net excellent at processing data in areas such as medical images, especially for image segmentation tasks in small samples and high-noise environments.

Based on these advantages, OphirGozes' team used a U-Net structure with VGG-16 as the encoder to provide two-dimensional lung cuts and pre-trained them on ImageNet [23]. U-Net performs segmentation predictions for each image slice to obtain a segmentation mask representing the lung region. A cropped area containing the lungs is then created by finding the bounding box that covers the largest area of the lungs on all slices. This can help the classifier focus more on the areas related to the lungs and eliminate interference from irrelevant areas, making the learning process of the classifier more efficient and accurate. After the training, the team connected the U-Net to the ResNet-50-2D deep convolutional neural network, which had been pre-trained on ImageNet, so that the two could work together [23].

Another team, Chuansheng Zheng’s team, A deep learning model called "DeCoVNet" was built. They pre-trained U-Net to extract a patient's 3D lung mask from CT images as input to DeCoVNet. Entering only a 3D lung mask helps reduce background information and better detection of COVID-19. It is worth mentioning that the research team used the unsupervised learning method [26] to segment the lung region, manually remove the failed cases, and use the remaining segmentation results as a ground-truth mask, which can effectively help improve the performance of the model. In the end, DeCoVNet showed quite a good performance, resulting in a ROC AUC value of 0.959. This study

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addresses several challenges, including the lack of systematic labeling of CT images by radiologists, and small area infections that may be overlooked by medical professionals [14]. DeCoVnet addresses weakly supervised COVID-19 detection by combining a spatial global pooling layer and a temporal global pooling layer, while leveraging the strengths of deep learning and pre-trained U-Net to generate 3D lung masks. The mask guided DeCoVNet to identify previously missed areas of infection [14].

3.2.2. Feature Pyramid Network. In addition to the above methods, Feature Pyramid Network (FPN) is also an excellent structure in COVID-19 image detection [16,20]. The design of FPN can effectively deal with multi-scale objects in images. This structure enables the network to understand the image content more comprehensively, improve the detection accuracy, and obtain better performance while maintaining the detection speed. Using FPN to classify and detect CT images shows its unique advantages. Because COVID-19 infection has different scales, FPN is better able to understand the infection point and identify small infected areas than other structures [16].

Mohammad Rahimzadeh's team built the FPN structure with ResNet50V2 as the backbone. After the same pre-training, the new model is compared with Xception and ResNet50V2. The findings demonstrate that the FPN structure markedly enhances the accuracy of COVID-19 diagnosis, achieving an overall accuracy of 98.49% and a sensitivity of 94.96%[16]. While FPNS meticulously detect infection points, conventional models like Xception and ResNet50V2 tend to misclassify normal images as COVID-19 by identifying any similarities as infections. This substantiates the superiority of FPN in this context.

Ying Song and her team also used FPN in the model they made, "DRENet". By using ResNet50 as the backbone for feature extraction of input graphics, FPN extracts top-K sub-images from global features, send them back to ResNet50 for connection with global features, and finally outputs image prediction. The advantage of this is that DRENet can extract the main focal features, especially the important disease features like ground glass shadow (GGO), which provides a visual aid for the doctor's auxiliary diagnosis [20].

4. Special methods

In addition to the aforementioned mainstream approaches, some teams have also employed alternative methods to apply deep learning in CT image recognition.

4.1. Multi-task Learning

Amine Amyar's team has proposed a new deep learning model for multi-task learning (MTL). This approach involves enabling the model to learn a broader and more abstract representation of features by tackling multiple tasks simultaneously, thereby enhancing the performance of each individual task. In this study, the research team utilized U-Net as the structure for both the encoder and decoder to address image reconstruction and segmentation tasks, ultimately improving image quality. Additionally, multilayer perceptrons were employed to classify images depicting COVID-19, normal cases, and other infections. The experimental findings suggest significant promise in image segmentation, indicating that employing the model to concurrently segment, classify, and reconstruct images can mutually enhance and elevate their individual performances [24].

4.2. Quantitative CT image parameter-Percentage of Lung Opacification

In the approach to COVID-19 testing, Lu Huan's team presented an innovative solution by deriving quantitative image parameters from CT scans using a deep learning model known as the percentage of lung opacification (QCT-PLO) [17]. Through experiments, the team demonstrated that there exists a significant variance in lung opacification percentages among normal individuals, COVID-19 patients, and individuals at varying stages of COVID-19 severity. Moreover, as the patient's condition deteriorates, the QCT-PLO values also change, thereby reflecting the patient's evolving condition. According to the parameters given by the model, doctors can judge the patient's current condition and subsequent treatment plan. In essence, QCT-PLO serves as an objective means to evaluate the impact of COVID-19 on patients' lungs, aiding doctors in making accurate diagnoses.

4.3. *Self-Trans*

Due to the particularity of medical images, obtaining a large amount of trainable data has always been a difficulty in deep learning in the medical field. To address this issue, Xuehai He's team introduced a method known as "Self-Trans" [12]. By integrating contrast-supervised learning principles [27] with transfer learning, this approach enables models to acquire learn powerful feature representations through self-supervised learning. These learned features can then be effectively transferred to different tasks or domains, mitigating the risk of overfitting and enhancing the model's generalization capabilities. Subsequent experiments have demonstrated that Self-Trans outperforms traditional transfer learning methods, particularly excelling when training data sets are limited. In such scenarios, models leveraging the Self-Trans approach exhibit superior accuracy compared to other deep learning models [12].

5. Conclusion

This paper outlines the utilization of deep learning technology for COVID-19 identification through computed tomography (CT) imaging and highlights emerging trends in related fields. With the global impact of the COVID-19 pandemic, conventional diagnostic methods face challenges in sensitivity and efficiency, whereas CT imaging offers early detection and characterization of COVID-19-related lung abnormalities. Deep learning models are increasingly applied to analyze CT images and aid in COVID-19 diagnosis, facilitating the advancement of computer-aided diagnosis systems.

The paper tracks the evolution of deep learning models in this domain, starting from initial applications focused on image classification and recognition to later advancements incorporating techniques like U-Net for image segmentation and feature pyramid networks. Innovations such as multi-task learning and quantitative CT image parameter analysis have shown significant success in enhancing the accuracy and reliability of COVID-19 diagnosis. Future research directions emphasize optimizing training datasets, refining model architecture, and integrating auxiliary methods to enhance diagnostic capabilities and support clinical decision-making for COVID-19 patients.

These studies deepen our comprehension of deep learning's role in medical imaging and offer a potent tool for COVID-19 diagnosis. As datasets expand and deep learning models evolve, we anticipate a more substantial impact of these approaches in COVID-19 diagnosis and treatment. Future research efforts should focus on enhancing model performance and promoting widespread clinical application to bolster doctors' decision-making processes and aid in controlling the spread of COVID-19.

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