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Detection of CT-image of COVID-19 using deep learning

Lenin Markshia.U, Siva sankar.C, Nawfal Nizam.R, Ramasamy.R, Vishnu Kumar.H

Department of Electronics and Communication Engineering, Francis Xavier engineering college, Tirunelveli, Tamil Nadu, India.

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ABSTRACT

Using computerized tomography (CT) images, this paper provides a methodical review of artificial intelligence (AI) and computer vision techniques for the diagnosis of the coronavirus illness of 2019 (COVID-19). We discovered after analyzing the earlier review studies that none of them included the classification and categorization of the COVID-19 literature according to computer vision tasks including detection, segmentation, and classification. Segmentation and classification tasks are used extensively in the majority of COVID-19 CT diagnosis techniques

1. INTRODUCTION

Caused by the novel coronavirus broke out between late 2019 and early 2020 acute respiratory disease is a new type of disease. On February 12, 2020, the World Health Organization (WHO) named it the Coronavirus Disease 2019 (COVID-19) [1], that has attracted considerable attention from the international communities [2]. COVID-19 is highly infectious, and the virus can spread through droplets and contact. As of June 22, 2020, approximately 9 million people have been infected around the world. Clinically, the virus has clinical manifestations of respiratory diseases, including cough, fever and lung inflammation [3], and it can also lead to acute respiratory distress syndrome as well [4- 8]. Although COVID-19 has a relatively lower mortality rate, its spread rate is astonishing [9,10], and it can even spread through asymptomatic virus carriers, compared with the previous severe acute respiratory syndrome (SARS) and Middle East respiratory syndrome (MERS)[11,12]. The common symptoms of COVID19 manifests fever, cough and dyspnea. In terms of susceptible people, espectially the aging people with comorbidities, the disease may cause fatal cadiopulmonary complications potentially[13]. Therefore, the early recognition of the disease can help individual patient to accept treatment quickly allow versatility.Incorporating a Neuro-Fuzzy Bayesian (NFS) classifier represents the next step in enhancing moving object detection. This hybrid approach combines fuzzy logic and Bayesian reasoning, proficiently addressing uncertainties and complex relationships within radar signals. The classifier adapts intelligently, considering dynamic and uncertain radar signals, blending Bayesian insights with fuzzy logic's interpretability.

In clinical practice, real-time reverse transcription polymerase chain reaction (RT-PCR) is the gold standard to diagnose the infection of COVID-19 [15]. RT-PCR technology detected ribonucleic acid in nasopharyngeal swabs and also confirmed COVID-19 patients. According to current clinical experiences, RT-PCR for the determination of viral RNA in sputum or nasopharyngeal swabs, has a high probability of early false negatives, so many suspicious patients must repeat the test every few days to finalize the diagnosis [16], and each test takes 48 hours. Therefore, this technology has various limitations, such as lack of kits, long detection time and lagging results [17]. Therefore, it is necessary to use CT scan images as an auxiliary detection method for COVID-19 screening

2. LITERATURE REVIEW

There were relevant studies on AI algorithm that was applied to the detection of COVID-19. From multiple sources, Qiu H [12] established a comprehensive data set of X-ray and CT scan images, and adopted deep learning and transferred learning algorithms to provide a simple and effective COVID-19 detection technology. A dual sampling attention network [20] was proposed to classify the different manifestations between COVID-19 and community-acquired pneumonia (CAP) infections. In order to focus on the lungs, a lung mask was applied to suppress the image context of non-lung regions in chest CT. At the same time, the online mechanism increased the focus on the deep learning model for the better focus on the lung infectious area. In this way, the model helps explain the evidence for the automatic diagnosis of COVID-19. The experimental results also proved that the proposed online attention refinement can effectively improve the classification performance. A quantitative system based on deep learning can automatically carry out CT segmentation of the chest CT infectious area and the entire lung, and establish a VBNet neural network, which can segment the COVID-19 infectious area in the CT scan image [19]. In order to accelerate the speed of data labeling, human-inthe-loop optimization was adopted to label each situation. Artificial intelligence (AI) algorithm is to combine the chest CT manifestations and clinical symptoms, exposure history, and laboratory tests to quickly diagnose COVID-19 positive patients. This study combines deep learning target detection and image classification methods to analyze and study the CT signs of COVID-19 patients' lesions, also, analyze the lesion characteristics at different stages. Based on the convolution of the time-space series, a fast detection algorithm model of the CT image lesion area is proposed, which can help the medical staff to perform the preliminary screening of COVID-19, shorten the hospitalization time of the patient, and reduce the risk of disease as well as reduce the risk of nosocomial infection to a certain extent. At the same time, the algorithm model proposed in this paper can obtain more reasonable reasoning results of CT signs of lesions through the correlation analysis of CT images of patients in different periods, help doctors to judge the condition quickly, and provide auxiliary basis for diagnosis and treatment. The remainder of the study is organized as follows. In Section II, related works are reviewed. In Section III, introducing the COVID-19 diagnosis method based on artificial intelligence followed by the details of each part. In Section IV, we describe the evaluations 45 based on the experimental results. In Section V, we summarize the proposed method and outline the study's conclusions.

3. RESEARCH METHODOLOGY

This paper analyzes and studies the desensitized CT images from 721 COVID-19 patients in different hospitals, and 600 images as training data for the detection model of COVID-19. The data set is displayed in Figure 1. The detection method for COVID-19 CT lesions is composed of three parts, including target area selection, object detection model and specific convolutional layers for spatiotemporal feature extraction. Figure 1. The data set of COVID-19 Note: Different scan layers of CT images of the same COVID-19 patient A. Segmentation of target areas The first step of lesion detection from COVID-19 CT images is to segment the lung areas. After the initial segmentation, some specific geometric morphology operations are then performed to obtain the required regions. We labeled lung contours scan-byscan on CT images from 50 patients with COVID-19 and other Authorized licensed use limited to: IEEE Xplore. Downloaded on February 12,2024 at 14:36:13 UTC from IEEE Xplore. Restrictions apply. 78 30 healthy people. The labeled sample is shown in Figure 2 and each image scan paired with its mask were prepared for training. In order to train a robust model, a part of training data is preenhanced with multiple geometric morphological data augmentations. According to the comprehensive analysis of data distribution, we performed multiple data enhancements around (-500, 1600) window-width-window-level to improve the stability of image segmentation. Due to the relevant features of target data, we designed a 2D lung areas segmentation model using encoder-decoder mode. The model consists of multiple continuous convolutional layers and pooling layers. Features are extracted all the way down, and feature fusion is used on the last convolutional layer to complete feature extraction by filling in missing information that is related to feature maps (such as position information, and edge information, etc.). The model completes preliminary segmentation of the lung field, as shown in Figure 3. Additional geometric morphological operations, such as corrosion, expansion, and hole filling provide the final region of interest(ROI) that is required by lesion detection. The above process reduces the extraneous areas for subsequent lesion detection, and significantly improves the model efficiency. Figure 2. Lung areas and the corresponding masks Note: The first column is the CT scan of the lung area; the second column is the mask corresponding to the lesion; the third column is the segmentation result of COVID-19. B. Lesion detection In lesion detection model, two specific advanced feature extractors in lesion detection model was designed: spatial semantic convolutional layer and time semantic convolutional layer. Due to the spatial continuity of CT images, there is a specific correlation between the spatially adjacent scans. In general, object detection focuses more on 2D feature association. Obtaining feature maps only in single-scan dimension will lose important spatial context, resulting in loss of detection accuracy. According to the CT imaging diagnosis guidelines of COVID-19, imaging signs were divided into three different periods including early stage, advanced stage, and severe stage. Many patients had corresponding data in different periods, and medical researches proved that there were some correlations among multiple-period imaging manifestations. If the transformation features from images with time dimension can be additionally extracted during the lesion detection, potential semantic information of the lesion signs at different stages may be mined. Although the accuracy was improved, the output of model could be more meaningful for auxiliary diagnosis. The design of spatial semantic convolutional layer was mainly a series of bidirectional recurrent 2D-convolutional operation set. Considering the spatial continuity of CT images, the closer scans may have higher correlation. The model captured image semantic information in batched scans through successive convolutional layers, and then added two spatial semantic convolutional layers to extract the spatially continuous features of lung. Afterwards, the feature maps from each layer were up-sampled as part of the input to the next two corresponding temporal semantic convolution layers. The time semantic convolutional layer was basically composed of several unidirectional recurrent 2D-convolutional operations. According to the researches on the COVID-19 CT image signal, it was more reasonable to extract the context semantic features in the unidirectional time dimension. Subsequently, these feature maps would go through two similar convolutional layers to complete the final extraction.

4. EXPERIMENT RESULTS

In order to verify the relationship between the complexity of the one-way time series convolution and the two-way time series convolution, the experiment created two model structures with only time sequence difference. The test data of the experiment consisted of the desensitized CT images of the remaining 121 COVID-19 patients and other 500 healthy people. The tested algorithm structure included Faster R-CNN, YOLO3, SSD, and the algorithm model based on space-time sequence convolution that was proposed in this paper—Space-time-Net, that was divided into two structures: one-way time series and two-way time series, abbreviated as Space-Time1 and Space-Time2. The same test data set was used to test the sensitivity of the patient identification and the accuracy of the target detection to the above model. For the verification of the effect of multi-stage image data on the experimental results, the test was divided into two stages. In the first stage, the images of each patient was collected at only one time point for testing. In the second stage, after the relevant supplement of the relevant images was completed, the patients with multi-stage image data were tested. Through the two-stage test, you can verify the influence of single spatial image and spatiotemporal sequence image on the accuracy of model, and evaluate whether the model can effectively apply the characteristics of temporal and spatial sequence to obtain more accurate test results. B. Analysis of experimental results The relevant data results of the first stage experiment was revealed in figure 4. Without the correlation of the patient's images in all stages, the difference in accuracy and sensitivity of YOLO3 was relatively large. The model proposed in this paper has good properties of accuracy and sensitivity under two structures (Space_Time1 and Space_Time2). By the experimental data in the first stage, it can be concluded that in the first testing stage, Space_Time2, with a time series bidirectional structure has higher target detection accuracy. It loses a certain degree of sensitivity for the complexity of the bidirectional sequence. Space_Time1 with a time series unidirectional structure has better sensitivity, indicating that the complexity of the algorithm model structure has a certain impact on the final effect of the model. The relevant data results for the second stage experiment were displayed in figure 5. When the images from all stages of patient were correlated, the difference in accuracy and sensitivity of YOLO3 was still relatively large. Compared with the experimental data in the first stage, the sensitivity and accuracy of the three comparison models improved. Under both structures, the model proposed in this paper revealed better accuracy and sensitivity than the first stage. Through the analysis of the model structure and the characteristics of experimental data, when the same patient has image data of multiple time periods, the time-space series convolutional layer of Space-Time-Net can extract the semantic features of the latent images related to it. The time series were valid and more accurate comprehensive test results were obtained. According to the analysis data from two sets of experiments, it can be concluded that the image data with time series attributes provided more semantic features of the images. In this paper, a time-space sequence convolution kernel extraction algorithm based on time-series was designed, and more accurate detection results were obtained. The trade-off between structural complexity and interpretability is the future optimization direction of the COVID-19 detection model.

5. CONCLUSION

The most accurate COVID-19 diagnoses are based on laboratory tests, such as RT-PCR. Patients infected or suspected of being infected with COVID-19 are typically admitted to the hospital for diagnostic procedures. These laboratory tests entail procedures that can be time- consuming, have low sensitivity, and have a high risk of false-negative results. Similarly, a shortage of equipment and strict testing standards have hampered the timely and accurate screening of suspected cases. Thus, non-laboratory examinations, such as computer-assisted imagery analysis of chest radiography (X-ray) or CT scans, are used to examine the lung regions to diagnose COVID-19. Specifically, CT image findings have been important for creating machine-based techniques to diagnose COVID-19. Implementing these methods is essential to contain the virus,screen out vast numbers of suspected and confirmed cases, and ease patient management in hospitals. Therefore, many chests CT–based AI and computer vision strategies have been developed for COVID-19 diagnosis. In this review study, we have reported and categorized the most well-known literature regarding the computer vision tasks of classification, segmentation, and detection. We also discussed the most well-known datasets utilized for COVID-19 CT research. According to our review study, AI- and deep learning–based models have been widely used to extract COVID-19-related infections from chest CT images. AI-enabled CT imaging methods can assist in automating the diagnosis process and reshaping the workflow while minimizing patient interaction and improving doctors' and radiologists' practices. Most of the COVID-19 diagnosis methods utilized classification techniques, while many COVID-19 prognostic models are based on segmentation. The most accurate COVID-19 diagnoses are based on laboratory tests, such as RT-PCR. Patients infected or suspected of being infected with COVID-19 are typically admitted to the hospital for diagnostic procedures. These laboratory tests entail procedures that can be time- consuming, have low sensitivity, and have a high risk of false-negative results. Similarly, a shortage of equipment and strict testing standards have hampered the timely and accurate screening of suspected cases. Thus, non-laboratory examinations, such as computer-assisted imagery analysis of chest radiography (X-ray) or CT scans, are used to examine the lung regions to diagnose COVID-19. Specifically, CT image findings have been important for creating machine-based techniques to diagnose COVID-19. Implementing these methods is essential to contain the virus,screen out vast numbers of

suspected and confirmed cases, and ease patient management in hospitals. Therefore, many chests CT–based AI and computer vision strategies have been developed for COVID-19 diagnosis. In this review study, we have reported and categorized the most well-known literature regarding the computer vision tasks of classification, segmentation, and detection. We also discussed the most well-known datasets utilized for COVID-19 CT research. According toour review study, AI- and deep learning–based models have been widely used to extract COVID-19-related infections from chest CT images. AI-enabled CT imaging methods can assist in automating the diagnosis process and reshaping the workflow while minimizing patient interaction and improving doctors' and radiologists' practices. Most of the COVID-19 diagnosis methods utilized classification techniques, while many COVID-19 prognostic models are based on segmentation approaches. There has been less attention given to computer vision-based detection algorithms for detecting COVID-19. A large number of diagnostic models produce relatively higher quantitative (SEN, SPE, ACC, etc.) outcomes due to their biased evaluations. There is a need for holdout test sets to avoid bias in evaluating a trained model. Further- more, there is a shortage of diverse and well-annotated datasets with additional clinical information. For instance, few datasets are available to train and test segmentation-based COVID-19 models. Ultimately, our review study supports the necessity for further research on the given topic in the future.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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