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COVID-19 detection based on Computer Vision and Big Data

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Abstract—For detecting COVID-19 and checking the severity of the patient's condition, CT examination of the lungs is significant. However, the current manual viewing of CT images requires professionalism. In order to improve the inspection efficiency of the huge number of CT images, it is necessary to develop an intelligent detection algorithm to perform CT inspections. This paper proposes a COVID-19 detection algorithm based on EfficientDet. EfficientDet leverages a faster and easier multi-scale fusion approach, which is more suitable for COVID-19 detection tasks with finer feature granularity. In addition, data augmentation is also significant in COVID-19 detection tasks. This paper verifies the effectiveness of EfficientDet on the SIIM-FISABIO-RSNA COVID-19 Detection dataset provided by Kaggle platform. Experimental results show that EfficientDet has achieved better performance than other detection algorithms. Taking MAP@0.5 as an indicator, EfficientDet reaches 0.545, which is 7.9% and 3.3% higher than the Faster RCNN algorithm and YOLO-V5.

Index Terms*—*COVID-19 Detection, EfficientDet, data augmentation, Big Data

I. Introduction

COVID-19 is a major new infectious disease, and the new crown pneumonia epidemic has undoubtedly had a profound impact on the normal operation of countries around the world. Revenues from industries such as retail catering, accommodation and tourism have fallen sharply. Manufacturing and real estate are slow to resume work and production due to liquidity constraints. The epidemic has brought different challenges to various industries. To meet the challenge, rapid testing for COVID-19 is particularly important. The computer-aided diagnosis system has a certain value for doctors to screen chest radiographs and judge the lesions. There are many patients who have serious CT examinations but negative nucleic acid tests. At this time, it is necessary to combine CT to diagnose through comprehensive analysis. CT can help doctors quickly determine whether a patient has pneumonia, what is its scope and degree, what stage the disease is in, and so on.

With the rapid development of artificial intelligence and big data technology, CT image pathology detection algorithms have also made significant progress. Common target detection models such as yolo and FPN have been applied in the direction of CT pathology detection. This type of detection model can achieve better performance if the resource is expanded, for example, the network depth, network width, and input image resolution. However, it is difficult to manually adjust the depth, width and resolution. In other words, the combination space is too large, manpower cannot be exhausted. In addition, the FPNs involves multi-scale fusion detection algorithms. When fusing different input features, it just adds the features without distinction. However, different input features have different resolutions, and their contributions to the fusion output features are often unequal. Based on the above considerations, this paper uses EfficientDet as the basic detection model for COVID-19 CT image detection. On the one hand, EfficientDet comprehensively considers network depth, network width, and input image resolution to achieve better performance. On the other hand, EfficientDet performs efficient multi-scale feature fusion, introducing learnable weights to learn the importance of different input features, and repeatedly applying top-down and bottom-up multi-scale feature fusion methods to improve model performance. In addition, we have implemented various data enhancement methods such as flip, crop, and rotation for the original data. Such methods have effectively improved the robustness of the model.

We experimented with EfficientDet on the SIIM-FISABIO-RSNA COVID-19 Detection dataset on the kaggle platform, and compared it with the popular target detection methods Faster RCNN and YOLO-V5. We also acknowledge Kaggle for providing Big-Data, free of charge. Kaggle offers a readable Big-Data-Environment. The experiment proved that EfficientDet and Faster RCNN and Compared with YOLO-V5, it can achieve more competitive performance.

In summary, the main contribution of this article is divided into two parts:

● For the COVID-19 Detection task, experiments were performed based on the lung medical CT image data set of the kaggle platform, and various data enhancements were made on the basis of the existing data, which effectively improved the robustness of the model.

● In order to efficiently integrate the multi-scale features of the network, while weighing the scale and performance of the network, a COVID-19 Detection network based on

EfficientDet is constructed. Using MAP@0.5 as an indicator, the performance of EfficientDet in the COVID-19 Detection task exceeds Faster RCNN and YOLO-V5.

A. *Related Work*

With the rapid development of artificial intelligence, especially deep learning, medical image analysis has developed rapidly. CT image pathology detection approaches based on deep learning emerge in endlessly. Mei et al. [1] designed a redundant channel pruning model based on YOLO, comprehensively considering the balance between the effectiveness and efficiency of the detector, and realized a lung nodule detector with both efficiency and accuracy, and named it YOLO-lung. George et al. [2] leveraged the DetectNet based on YOLO to detect nodules in lung CT scans. Among them, object detection is regarded as a regression task, and a single convolutional network predicts multiple bounding boxes and the class probabilities of these boxes at the same time. Li et al. [3] proposed a location-aware attention network named Mvp-net, which combined medical prior knowledge to explicitly model multiple windows specified by doctors.Mvp-net leveraged a multi-view feature pyramid network to handle different deep features. Rahimzadeh et al. [4] proposed a high-speed and accurate automatic COVID-19 detection framework. The first stage of this framework is to analyze chest CT images and discard low-quality samples. In the second stage, a new feature pyramid network is introduced to improve the fine-grained classification performance. Shao et al. [5] proposed a multi-scale booster (MSB) that integrates channel and spatial attention into the backbone network. In each pyramid level, MSB captures fine-grained scale changes by using hierarchical dilated convolution. At the same time, the channel and spatial attention mechanism increase the network's ability to select relevant feature responses for lesion detection. Shakeel et al. [6] proposed an automatic lung cancer detection method. This method demonstrated that lung cancer image preprocessing is a significant stage, including edge detection, lung image resampling and image denoisin. After that, a deep neural network trained on the fly is utilized to predict lung cancer. Gozes et al. [7] developed a weakly supervised deep learning framework, which includes multiple approaches such as localization and classification. The framework also utilized limited annotations to detect and measure the severity of COVID-19 disease from chest CT scans. Horry et al. [8] combined the three most commonly medical imaging modes for multi-modal learning, which including X-Ray, Ultrasound and CT image.Then utilized all three modal information as network input for COVID-19 detection. Alom et al. [9] proposed a multi-task method that utilized an initial residual recurrent convolutional neural network based on transfer learning, and utilized the NABLA-N model for COVID-19 lesion segmentation. Alshazly et al. [10] discussed how a DNN trained on chest CT images can diagnose COVID-19 infected persons in a fast and automated process, and proposed a custom method tailored for each model.The migration learning strategy and the visualization results proved that this method can not only identify COVID-19 cases, but also accurately locate COVID-19 related areas.

The rest of this paper is expanded as follows. The second section mainly introduces the specific principles of EfficientDet and related application details, as well as data augmentation strategies. The third section mainly introduces the results and analysis of the COVID-19 detection experiment with EfficientDet. The fourth section is a summary of this paper, and finally is the acknowlegement.

II. YOLO V5 ALGORITHM

The main contribution of EfficientDet is to extend the idea of EfficientNet compound scaling, clarify the architectural decision into a scalable framework, and achieve a balance between speed and accuracy. The the structure EfficientDet is shown in Figure 1.

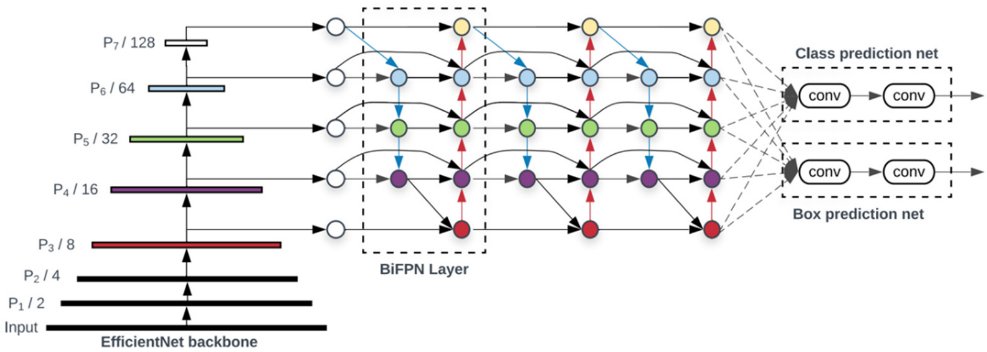

Figure 1. The Structure of EfficientDet

EfficientDet consists of four parts: EfficientNet Backbone, BiFPN layer, Class and Box prediction net. EfficientDet belongs to single-shot detectors. The 3-7 level {P3, P4, P5, P6, P7) features in the backbone network will be passed to the feature network, And repeatedly apply two-way(top-down & bottom-up) feature fusion. These fused features are fed to the class prediction and bounding box prediction network to generate object classes and bounding box positions. The repeated weighted bidirectional feature pyramid network BiFPN proposed by EfficientDet is one of the cores of EfficientDet. Compared with PANet [11], the node with only one input edge is deleted, and if the original input node and output node are in the same layer, BiFPN will add an extra edge between the original input node and the output node. In addition, BiFPN treats each two-way path as a feature network layer, and reuses the same layer multiple times to achieve higher-level feature fusion. The specific times are searched through NAS.

In addition, the data augmentation utilized in this paper is of great help to the improvement of model performance. Data augmentation includes random brightness enhancement, random Gaussian blur, random rotation, random translation, random horizontal flip and random scale scaling. The random probability of each data augmentation method will be introduced in Section III.

III. EXPERIMENTS

a) Dataset

The SIIM-FISABIO-RSNA COVID-19 Detection dataset [12] contains 6,334 chest scan samples in DICOM format. To protect patient privacy, these samples have been desensitized. All samples are labeled by a team of experienced radiologists. The published dataset is divided into training set and testing set according to the ratio of 4:1. Samples of the dataset are shown in Figure 2.

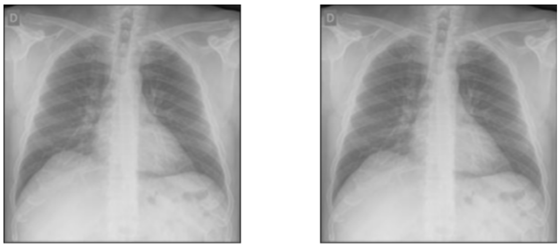

Figure 2. Samples of the dataset

b) Evaluation Index

We utilize mAP@0.5 as the evaluation index. mAP@0.5 means that the prediction is correct if the Intersection over Union between the prediction result and ground truth exceeds 50%. The calculation formula of Intersection over Union is as formula (1).

$$IoU = \frac{\text{Area of Overlap}}{\text{Area of Union}} \tag{1}$$

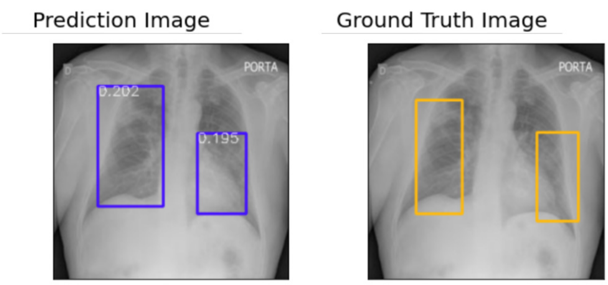

Figure 3. GT and the prediction of EfficientDet

c) Details and Analyze

During the training process, the optimizer is SGD, the learning rate is set to 5e-3, the batchsize is set to 32, and the epochs is set to 10. The probability of random rotation and random brightness augmentation is set to 0.3, and the probability of random translation, random horizontal flip and random scale scaling is set to 0.5.The experimental results of the three detection algorithms including EfficientDet, Yolo v5 and Faster RCNN are shown in Table 1. The comparison between EfficientDet prediction results and ground truth is shown in Figure 3.

As can be seen from Table 1, EfficientDet has achieved better performance than other detection algorithms. Taking MAP@0.5 as an indicator, EfficientDet reaches 0.545, which is 7.9% and 3.3% higher than the Faster RCNN algorithm and YOLO-V5. This paper analyzes the reason for the better performance of EfficientDet because BiFPN allows simple and fast multi-scale feature fusion, which is more suitable for fine-grained pathological detection problems.

Table 1. Comparison of different algorithms on mAP@0.5

Models	mAP@0.5
Yolo v5	0.512
Faster RCNN	0.466
EfficientDet	**0.545**

IV. CONCLUSIONS

In this paper, for the COVID-19 Detection task based on CT images, experiments are carried out on the basis of the EfficientDet detection model with fast multi-scale feature fusion capability. At the same time, a variety of random data augmentation methods including translation and rotation are utilized to enhance the robustness of the model. Experiments verify that the fast multi-scale feature fusion method is effective in the COVID-19 Detection task. With MAP@0.5 as the indicator, EfficientDet has achieved more competitive performance than Faster RCNN and YOLO-V5.

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REFERENCES

[1] Mei S, Jiang H Q, Ma L. YOLO-lung: A Practical Detector Based on Imporved YOLOv4 for Pulmonary Nodule Detection[C]//2021 14th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics (CISP-BMEI). IEEE, 2021: 1-6.

[2] George J, Skaria S, Varun V V. Using YOLO based deep learning network for real time detection and localization of lung nodules from low dose CT scans[C]//Medical Imaging 2018: Computer-Aided Diagnosis. International Society for Optics and Photonics, 2018, 10575: 105751I.

[3] Li Z, Zhang S, Zhang J, et al. Mvp-net: Multi-view fpn with position-aware attention for deep universal lesion detection[C]//International Conference on Medical Image Computing and Computer-Assisted Intervention. Springer, Cham, 2019: 13-21.

[4] Rahimzadeh M, Attar A, Sakhaei S M. A fully automated deep learning-based network for detecting covid-19 from a new and large lung ct scan dataset[J]. Biomedical Signal Processing and Control, 2021, 68: 102588.

[5] Shao Q, Gong L, Ma K, et al. Attentive CT lesion detection using deep pyramid inference with multi-scale booster[C]//International Conference on Medical Image Computing and Computer-Assisted Intervention. Springer, Cham, 2019: 301-309.

[6] Shakeel P M, Burhanuddin M A, Desa M I. Lung cancer detection from CT image using improved profuse clustering and deep learning instantaneously trained neural networks[J]. Measurement, 2019, 145: 702-712.

[7] Gozes O, Frid-Adar M, Sagie N, et al. A weakly supervised deep learning framework for covid-19 ct detection and analysis[C]//International Workshop on Thoracic Image Analysis. Springer, Cham, 2020: 84-93.

[8] Horry M J, Chakraborty S, Paul M, et al. COVID-19 detection through transfer learning using multimodal imaging data[J]. IEEE Access, 2020, 8: 149808-149824.

[9] Alom M Z, Rahman M M, Nasrin M S, et al. COVID_MTNet: COVID-19 detection with multi-task deep learning approaches[J]. arXiv preprint arXiv:2004.03747, 2020.

[10] Alshazly H, Linse C, Barth E, et al. Explainable covid-19 detection using chest ct scans and deep learning[J]. Sensors, 2021, 21(2): 455.

[11] Liu S, Qi L, Qin H, et al. Path aggregation network for instance segmentation[C]//Proceedings of the IEEE conference on computer vision and pattern recognition. 2018: 8759-8768.

[12] Wiersinga, W. Joost, et al. "Pathophysiology, transmission, diagnosis, and treatment of coronavirus disease 2019 (COVID-19): a review." Jama 324.8 (2020): 782-793.