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A Noise-Resilient Framework for Automatic COVID-19 Pneumonia Lesions Segmentation from CT Images

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Abstract: *The coronavirus disease pandemic of 2019 (COVID-19) is sweeping the globe. Medical imaging, such as X-ray and computed tomography (CT), is critical in the global fight against COVID-19, and newly developed artificial intelligence (AI) technologies are enhancing the power of imaging tools and assisting medical specialists. We examine the rapid responses to COVID-19 in the medical imaging community (enabled by AI).Although deep learning algorithms have shown promise in a number of areas, they continue to struggle with noisy-labeled images throughout the training phase. Given that the quality of annotation is inextricably linked to a high level of knowledge, the issue is even more pressing in the medical picture arena. It's still a big difficulty to get rid of the noise from noisy labels for segmentation tasks without adding more annotations. As a noninvasive imaging technique, computed tomography (CT) can detect certain lung symptoms linked with COVID-19. As a result, CT could be a useful tool for early detection and diagnosis of COVID-19. Despite its benefits, CT may have some imaging characteristics in common with COVID-19 and other kinds of pneumonia, making differentiation challenging. Due to its high power of feature extraction, artificial intelligence (AI) leveraging deep learning technology has recently proven remarkable success in the medical imaging arena. Deep learning was used to detect and distinguish between bacterial and viral pneumonia in paediatric chest radiographs.For the segmentation challenge, we present a novel noise-resistant architecture for learning from noisy labels. To better deal with lesions of varied scales and appearances, we present a unique COVID-19 Pneumonia Lesion segmentation network (COPLE-Net), which is a generalisation of Dice loss for segmentation and Mean Absolute Error (MAE) loss for robustness against noise. The noise-resistant Dice loss and COPLENet are combined with an adaptive self-ensembling architecture for training, in which a student model's Exponential Moving Average (EMA) is employed as a teacher model that is adaptively updated by suppressing the contribution. In the context of learning from noisy labels for COVID-19 pneumonia lesion segmentation, our system with adaptive self-ensembling outperforms a regular training method and outperforms existing noise-robust training approaches.*

Keywords: CT, Deep Learning, COVID-19, Noisy Label, Segmentation, Pneumonia, Medical Image Annotation.

I. INTRODUCTION

The severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2)-caused coronavirus illness 2019 (COVID-19) is an ongoing pandemic. The number of persons who have been affected by the virus is fast rising. There have been 1,133,758 cases of COVID-19 recorded in over 200 countries and territories as of April 5, 2020, leading in about 62,784 deaths (a fatality rate of 5.54 percent) [1]. The World Health Organization (WHO) labelled the outbreak a Public Health Emergency of International Concern (PHEIC) on January 30, 2020, and recognised it as a pandemic on March 11, 2020, causing widespread public health concern around the world.

In most cases, a reverse-transcription polymerase chain reaction (RT-PCR) is used to confirm the diagnosis (RT-PCR). However, it has been suggested that the sensitivity of RT-PCR may not be sufficient for early detection and treatment of suspected patients (5,6). As a noninvasive imaging technique, computed tomography (CT) can detect specific lung symptoms linked with COVID-19 (7,8). As a result, CT could be a useful tool for early detection and diagnosis of COVID-19. Despite its benefits, CT may have some imaging characteristics in common with COVID-19 and other kinds of pneumonia, making differentiation challenging. To deal with lesions at different scales, we propose a new COVID-19 Pneumonia Lesion Segmentation Network (COPLE-Net).

We present a novel noise-robust Dice loss function and integrate it into a self-ensembling architecture, where an adaptive teacher and an adaptive student are introduced to further improve the performance in dealing with noisy labels, in order to make the training process resilient against noisy labels. COVID-19 Pneumonia Lesion Segmentation Network technique, Noise-robust Dice Loss method, and Noise-robust Adaptive Self-ensembling method were employed in this pa-per.We compared our proposed framework to two other meth-ods for dealing with noisy labels: data re-weighting, which treats samples with large training loss values as noisy labels that should be suppressed, and data re-weighting, which treats samples with large training loss values as noisy labels that should be suppressed. We used the 90 percent of the training loss in the last 100 steps as a threshold, and samples with loss values greater than that exsting technique were ignored, similar to our adaptive instructor. Label update: predicts new labels for training images using an ensemble of five models trained with the initial annotations, then retrains the network using the new

labels. COPLE-Net trained with Dice loss implemented both the data re-weighting and label update procedures, and this is referred recognised as the baseline. Our adaptive approach was used to compare them.They were compared to our COPLE-Net and LND-Dice adaptive self-assembly architecture. Results of quantitative examination of various training methods. Both data reweighting and label update are shown to improve segmentation performance over the baseline, and our suggested framework surpasses these methods with the greatest average Dice and lowest average RVE and HD95, respectively. These methods were tested on different lesion groups, demonstrating that our method outperforms the others when dealing with lesions of various scales.

1.1 Motivation

To identify COVID-19 Pneumonia Lesions we are used a Noise-robust Framework based on CT Images. This framework is a combination and generalisation of MAE loss that is robust against noisy labels and Dice loss that is insensitive to foreground-background imbalance , and it deals with noisy annotations for training CNNs to segment COVID19 pneumonia lesions. Our strategy has the potential to ease the restricted availability to high-quality pixel-level labels provided by experts for large-scale 3D picture collections, as well as the annotation load. Our noise resilient Dice loss function is unique in that it is not dependent on a single CNN and can be used with a variety of training methodologies, including the normal training procedure and our self-ensembling architecture.

1.2 Objectives

- To do an extensive study by COVID-19 Pneumonia Le-sions from CT Images based on Noise-robust Framework for Automatic Segmentation.
- To Design of Noise-robust Framework for Automatic Segmentation.
- To Design Of Noise-robust Framework to improve the performance of dealing with noisy labels, we integrate our COPLE-Net and LNR-Dice into a self ensembling framework.
- To Implement Noise-robust Framework in which pro-posed an unique noise-resistant Dice loss function and include it into a self-ensembling system that includes an adaptive instructor and an adaptive student to increase performance when dealing with noisy labels.

II. History & Background

Many literature is available for different COVID-19 Pneumonia Lesions from CT Images using different tech-niques. Various papers are suggesting the various implemen-tation ways as illustrated and discussed below.

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P. Saleem and M. Arif et.al., proposed the work on Plant Disease Detection and Classification by Deep Learning. In this Paper,A more efficient means of seeing disease spots in plants should be developed because it will save money by reducing the use of fungicides, pesticides, and herbicides that aren't needed. Because the severity of plant diseases varies over time, DL models should be enhanced or adjusted to allow them to identify and categorise illnesses during their entire life cycle.

F. Shi, J. Wang,et.al., proposed the work on Review of Artificial Intelligence Techniques in Imaging Data Acquisition. Tin this paper, they explore how AI can provide safe, accurate, and efficient imaging solutions in COVID-19 applications in their study. COVID-19 examines intelligent imaging systems, clinical diagnostics, and groundbreaking research in depth, covering the complete pipeline of AI-powered imaging applications. To illustrate the efficiency of AI-empowered medical imaging for COVID-19, two imaging modalities, namely X-ray and CT, are used. It's worth remembering that imaging only gives you a partial picture of COVID-19 patients. To aid in the screening, identification, and diagnosis of COVID-19, imaging data should be combined with clinical symptoms and laboratory examination results.

Lu Huang, MD, PhD ,et.al., proposed the work on Serial quantitative chest CT assessment of COVID-19: Deep-learning approach. In this study, The estimation of COVID-19 lung opacification evaluated on chest CT using a commercially available deep-learning-based technology was significantly different among different clinical severity groups in this investigation. In COVID-19, this technique has the ability to remove subjectivity in the initial assessment and follow-up of pulmonary results.

F. Shan,et.al., proposed the work on Lung infection quantification of COVID-19 in CT images with deep learning. A DL-based segmentation technique was built in this study to automatically segment and quantify infection areas in COVID-19 patients' CT scans. For automatic infection region definition and POI measurements, quantitative examination revealed high accuracy.

Y. Cao, Z. Xu, J. Feng,et.al., proposed the work on Longitudinal assessment of COVID-19 using a deep learning–based quantitative CT pipeline. In this researcher, a convolutional neural network based on the U-Net architecture was created. We used this pipeline to examine the contrasting evolution of two confirmed cases of COVID-19 from Wuhan, China, that were receiving similar supportive therapy, as well as the potential of deep learning–based quantitative CT for providing objective assessment of pulmonary involvement and therapy response in COVID-19, but more research is needed to determine how well such an approach performs in this scenario.

D. Karimi, H. Dou,et.al., proposed the work on Deep learning with noisy labels : exploring techniques and remedies in medical image analysis. In this study, we looked at three different types of label noise in medical imaging datasets, as well as the relative efficiency of various different approaches for reducing label noise's detrimental impact. Label noise in medical imaging has a variety of sources, statistics, and strengths, and our research reveals that the effects of label noise should be carefully considered while training deep learning systems. This calls for more research and the creation of strong models and training techniques.

H. Zhu, J. Shi,et.al., proposed based on Pick-and-Learn, Automatic quality evaluation for noisy-labeled image segmentation. In this paper, Label quality evaluation approach is a method for tuning the segmentation network on noisy-labeled datasets that consists of three parts: segmentation module, quality awareness module, and overfitting control module. The overfitting control module can keep the network's generalisation while the quality awareness module evaluates the relative quality of the labels in the mini-batch and re-weights them. When compared to models that do not use this strategy, our quality awareness model maintains good segmentation accuracy as noise levels rise.

J. Chen, L. Wu, J. Zhang,et.al., proposed work based on Deep learning-based model for detecting 2019 novel corona virus pneumonia on high-resolution computed tomography: a prospective study. In this work, the deep learning-based model outperformed expert radiologist performance in a fraction of the time. It has a lot of promise to increase diagnosis accuracy, relieve strain on frontline radiologists, speed up the diagnosis, isolation, and treatment of COVID19 patients, and so help contain the epidemic.

S. Min, X. Chen,et.al., proposed work based on A two-stream mutual attention network for semi-supervised biomedical segmentation with noisy labels. We present a two-stream mutual attention network (TSMAN) that is resistant to noisy labelling in this research. During the parameter update process, this network detects inaccurate labels and reduces their influ-ence. Our hierarchical distillation takes advantage of both data and model distillations by hierarchically integrating these two methods to increase the quality of pseudo labels. Finally, using self-training to combine TSMAN and hierarchical distillation results in state-of-the-art performance on the HVSMR 2016 and Brats 2015 benchmarks.

Y. Pang, Y. Li, J. Shen,et.al., proposed work based on Towards bridging semantic gap to improve semantic segmentation. In this study, we presented a bottom-up parallel pyramid for aggregating multi-level features. Two solutions for bridging the semantic gap have been investigated and are included in our parallel pyramid. To reduce the semantic discrepancy between multi-level features, one method is to improve the representation capabilities of shallow features. The other approach is to find complimentary information in extremely shallow features in order to improve deep features. As a result, SeENet outperforms other state-of-the-art approaches on a variety of benchmark datasets, demonstrating the effectiveness of our technology.

III. Design Issues

In this Deep learning techniques, the fight against COVID-19, this techniques has emerged as the most effective strategy. The image data in COVID-19 applications, on the other hand, may include partial, inexact, and erroneous labels, making it difficult to train an appropriate segmentation and diagnostic network. Weakly supervised deep learning algorithms could be used in this fashion. Furthermore, manually classifying imaging data is costly and time-consuming, prompting researchers to look into self-supervised deep learning and transfer-deep-learning methods. COVID-19 multi center research should also be encouraged.COVID-19 is caused by a corona virus and has imaging properties that are comparable to pneumonia caused by other viruses. We were unable to choose other viral pneumonias for comparison in this investigation due to the lack of laboratory confirmation of the aetiology in each of these cases. The lack of transparency and interpretability is a drawback of all deep learning approaches.

While we utilised a heatmap to visualise the relevant regions in the photos that led to the algorithm’s decision, heatmaps aren’t enough to see what unique traits the model uses to differentiate between COVID-19 and CAP. During testing, one sub-network may not be enough to complete all conclusions. This can be accomplished by creating attention maps and then applying them to feature map gradients during the training process. It was also necessary to investigate the consequences of using various sub-networks, which may add to the difficulty of developing attention models.

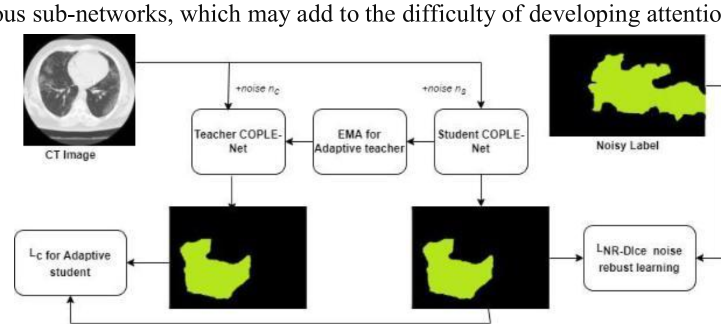

Figure 1: Noise-robust framework for COVID-19 pneumonia lesion segmentation with noisy training labels

With noisy training labels, the suggested noise-resistant framework for COVID-19 pneumonia lesion segmentation is provided. It is made up of three parts: a noise-resistant Dice loss, a noise-resistant Dice loss, and a noise-resistant Dice loss. LNR-Dice is a unique network. COPLE-Net and adaptive self-assembly, with the teacher model T being an exponential moving average of the student model S that is adaptively updated based on S’s performance. Student S learns from instructor T adaptively through a consistency loss LC, i.e. only when T outperforms S.

3.1 Mathematical Model

The noise-robust framework for learning from noisy labels for automatic segmentation of COVID-19 pneumonia lesion Network, in which we are used different method as mentioned in below:

A. COVID-19 Pneumonia Lesion Segmentation Network: The performance of versions of UNet with an encoder-decoder structure is the inspiration for our proposed COPLE-Net. We offer dual pooling as down-sampling, which has a lower information loss than basic max-pooling. To bridge the semantic gap between low-level and high-level features, we replace the traditional skip connection between the encoder and decoder with a bridge layer that maps low-level encoder features to a lower dimension before concatenating them with high-level encoder features. Third, we add an Atrous Spatial Pyramid Pooling (ASPP) module at the encoder-decoder structure's bottleneck to better segment lesions at different scales. The ASPP comprises of four parallel layers of dilated convolution with variable dilation rates. Their outputs are concatenated so that the network can collect multi-scale information for segmentation of tiny and large lesions more effectively. Our approach results in a smaller number of parameters and improved efficiency. When utilising a down-sampling layer, the channel number in COPLE-first Net's resolution level is C, and it is doubled each time.

B. Noise-robust Dice Loss: When trained with a standard image classification loss function, such as cross entropy, pneumonia lesions often occupy a tiny section of the picture at an early stage, causing the CNN's prediction to be significantly skewed towards the background. Milletari et al. suggested the Dice loss function to solve this problem by implicitly maintaining a balance between foreground and background classes:

LDice = 1 2 PN i pigi PN i p 2 i + PN i g 2 i = PN i (pi gi) 2 PN i p 2 i + PN i g 2 i

where N is the image's pixel count. gi is the equivalent value acquired from the binary training label, and pi is the foreground probability of pixel I predicted by the CNN. The numerator assigns higher weights to pixels with larger prediction errors, making LDice a version of Mean Square Error (MSE).For segmentation, the MAE loss can be recast as:

LMAE = PN i —pi gi — N

LMAE treats each pixel equally, despite its tolerance for noisy labelling, and performs poorly with deep CNNs and hard datasets. In segmentation tasks, it is likewise unable to deal with the foreground-background imbalance. We present a unique noise-robust Dice loss LNR-Dice that is a generalisation of LDice and LMAE to take advantage of the advantages of LDice and LMAE while overcoming their limitations: LNR-Dice = PN i —pi gi — PN i p 2 i + PN i g 2 i + where [1.0, 2.0] is a hyper-parameter and = 105 is a small integer to ensure numerical stability. LNR-Dice equals the Dice loss LDice when = 2.0. LNR-Dice becomes a weighted variant of LMAE when = 1.0.The suggested LNR-Dice is not equivalent to just utilising LMAE + LDice (i.e., linear combination of MAE and MSE), because the LMAE term is still not suited for deep CNNs and biassed towards the background class, and the MSE in LDice is still sensitive to noise. As a result, our suggested LNR-Dice is better suited for segmentation tasks involving noisy labels and deep CNNs than LMAE + LDice.

C. Noise-robust Adaptive Self-ensembling: We combine our COPLE-Net and LNR-Dice into a self-ensembling framework that was originally presented for semi-supervised learning to improve the performance of coping with noisy labels. It's made up of a teacher model T and a student model S, both of which have the same CNN structure, and it's updated as a S:

EMA. t = t1 + (1)t

In this method, we presented parameter T and S for * and .In this study, our COPLE-Net implements T and S and COPLE-Net implements T and S.The teacher model T is more stable than the student model S as a result of EMA, and it can be used to oversee S via a consistency loss Lc.The total loss function for training is: Let x and y represent a training image and its noisy annotation, respectively.

L = Lseg (S(x + s), y) + Lc (S(x + s), T(x + t))

where s and t are random Gaussian noises applied to S and T's inputs for data augmentation, respectively. Lseg is a segmentation loss that LDice or LNR-Dice can implement. Lc is a consistency loss that MAE uses because of its resilience to encourage T and S to deliver near predictions. Lc has a weight of zero.First, we propose an adaptive teacher that suppresses S's contribution to T (i.e., EMA) when S performs poorly with significant training loss values, which could be due to noisy labelling. This is accomplished by making the value of a function of S's training loss: = (0 , if Lseg S(x + s), y ¡ 1.0, otherwise (6) where 0

where 0 denotes the normal EMA parameter when S has an excellent performance with minimal training loss. Adaptively set as the p-th percentile of the student model's loss during the last K (i.e., 100) training steps, is a dynamic threshold value for S's segmentation loss. When the loss of S exceeds at one training step due to noisy labels, the teacher model T is not updated by S at that step.

We suggest an adaptive student model in which T's super-vision on S is suppressed when T's performance is lower than S's, which is implemented by making the value of dependent on S and T's performance: = (0 , if Lseg T(x + t), y ¿ Lseg S(x + s), y 00 , otherwise where 0 is set in the same way as typical self-ensembling frameworks (e.g., 0.1) [20], [21] when

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T performs better than S. 00 = 0.1 0 is a small number to suppress the weight of the consistency loss Lc when T does not outperform S.

IV. Results And Analysis

Experiments were conducted using clinical CT images of 558 COVID-19-infected pneumonia patients from ten different institutions. Slice thickness/inter-slice spacing ranged from 0.625 mm to 8.0 mm in the photos, with pixel sizes ranging from 0.61 mm to 0.93 mm. We divided the photos into 378, 50, and 130 groups at random for training, validation, and testing. 52489, 6556, and 17205 were the slice numbers for training, validation, and testing, respectively. Annotations for the training photos were collected using a human-in-the-loop technique similar to that described in, in which an initial model trained on a short dataset generated pseudo labels for the training images, which were then modified by non-expert researchers into annotations. We calculated the Dice similarity, Relative Volume Error (RVE), and the 95th percentile of Hausdoff Distance (HD95) between segmentation results and the ground truth in 3D space for quantitative evaluation.

Dice(Ra, Rb) = 2—Ra Rb— —Ra—+—Rb— RV E(Ra, Rb) = abs(—Ra——Rb—) —Rb—

The region partitioned by a CNN and the ground truth, respectively, are represented by Ra and Rb.

HD0 (Sa, Sb) = max iSa min jSb ——i j——2 (10) HD(Sa, Sb) = max HD0 (Sa, Sb), HD0 (Sb, Sa)

A quantitative comparison of these networks for each group of test photos, demonstrating that our proposed COPLE-Net outperformed the others for lesions of various sizes. It shows that COPLE-Net outperforms the competition when dealing with lesions of various sizes. According to grid search based on the validation set, we set 0 = 0.1 and to the 90th percentile of S's segmentation loss over the past 100 steps. Our proposed framework took 5.3 hours to train, and it took 4.242.83 seconds to infer one 3D picture. The model was trained and then deployed on the SenseCare platform to assist clinic research.

The suggested adaptive self-ensembling architecture was used to further train our COPLE-Net. For the ablation investigation, we began by training our COPLE-Net with Dice loss, progressively adding self-ensembling with standard mean teacher, our adaptive teacher, and adaptive student, and eventually combining our COPLE-Net, LNR-Dice, and adaptive self-ensembling. The average Dice score improved from 78.61 percent to 79.36 percent while utilising self-ensembling with standard mean instructor compared to the baseline. The usage of an adapted instructor and an adaptive student resulted in increased accuracy. When trained with the same Dice loss as the aforementioned variations, our adaptive self-ensembling combining adaptive teacher and adaptive student surpassed them, attaining an average Dice score of 80.09 percent. Finally, when integrated with our LNR-Dice, the suggested framework produced average Dice of 80.72 percent, RVE of 15.96 per-cent, and HD95 of 17.12 mm, which is much better than the baseline.

V. Conclusion

In this paper ,We deal with COVID-19 pneumonia lesion segmentation from CT images using noisy labels because clean labels are difficult and expensive to get. We begin by introducing LNR-Dice, a noise-resistant Dice loss function that is an extension of MAE loss that is resistant to noisy labels and Dice loss that is unaffected by foreground-background imbalance. The COVID-19 Pneumonia Lesion Segmentation Network (COPLE-Net) is then proposed, which incorporates various light-weight modules for improved performance. They're integrated with a novel adaptive self-ensembling framework, in which we incorporate an adaptive teacher and an adaptive student to counteract the training effect of noisy labels. We employed noisy labels in real life to validate the effectiveness of our suggested strategy, unlike earlier studies that used simulated noisy labels for tests. However, in the future, it would be interesting to study the efficacy of our system across a wider range of noise levels.

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