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Deep learning Algorithm To Classify Coronavirus (COVID-19) By Estimating Infected Region Present In The Computed Tomography (CT) Images

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Abstract -
The Coronavirus Disease (COVID -19) has caused more than 2.5 million deaths across the globe so far, and it is still increasing. To curtail the growth of this virus, screening and testing large number of suspected cases for treatment is a priority. The traditional pathogenic testing is the gold standard but its very time consuming with significant false results. Alternative way for diagnostics is necessary and urgent need to combat this disease. The Chest Computed tomography (CT) provides a more Trustworthy and accurate in Classifying (COVID-19) compared to traditional testing, diagnosing CT scans involve radiology experts, medical experts and is very time consuming especially during the pandemic time. However, Deep learning has been proved as a popular and powerful method in many medical imaging diagnosis areas. In this paper, We propose a Deep learning algorithm which is capable of and classifying the chest computed tomography (CT) of (COVID-19) among the chest computed tomography (CT) of Viral-Pneumonia by Estimating the infected regions in the radiographs and provide a clinical diagnosis ahead of lab tests and saving time for disease control.

Key Words: image-Segmentation, computed tomography ,COVID-19, image-enhancement ,CNN, Deep Learning

1.INTRODUCTION

The novel coronavirus (nCoV) infection first identified in Wuhan, China, and has extensively spread all over the world since January 2020 [3]. Coronaviruses (CoV) are a large family of viruses that cause illness ranging from the common cold to more severe diseases such as Middle East Respiratory Syndrome (MERS-CoV) and Severe Acute Respiratory Syndrome (SARS-CoV) [1]. A novel coronavirus (nCoV) is a new strain that has not been previously identified in humans. World Health Organization (WHO) declared the outbreak of nCoV as a “Public Health Emergency of International Concern” on 30 January 2020[2]. World Health Organisation named this disease as coronavirus disease (COVID-19) February 2020. To date, COVID-19 had spread to almost 235 countries and territories due to its highly infectious nature. Moreover, there is no vaccine or Food and Drug Administration (FDA)-approved drug [2]. To date (1 April 2020), there are 859,965 confirmed cases all around the world with 42,344 deaths and 178,364 recovered. COVID-19 severely affected the USA (188,592 cases), Italy (105,972 cases), Spain (95,923 cases), China (81,554 cases), Germany (71,808 cases), France (52,128 cases), and Iran (44,605 cases). The second largest population country in the world, i.e., India, is also affected from COVID-19 and 1718 confirmed cases with fifty-two deaths on 1 April 2020 [4].There is a vital need to detect the disease at early stage and instantly quarantine the infected people due to unavailability of specific drugs for COVID-19. The Chinese Government reported that the diagnosis of COVID-19 is confirmed through real-time polymerase chain reaction (RT-PCR) [5]. However, RT-PCR suffers from high false-negative rates and time-consuming. The low sensitivity of RT-PCR is not acceptable in the current epidemic situation. In some cases, the infected people may not be recognised and get suitable treatment on time. The infected people may get spread the virus to healthy people due to communicable nature of nCoV. It is observed from clinical reported of infected peoples that there is bilateral change in chest computed tomography (CT) images [6]. Therefore, chest CT has been used as alternative tool to detect the infection caused by nCoV due to high sensitivity [7]. The National Health Commission of China reported that chest CT can be utilised to detect the infection caused by nCoV [5].

2.RELATED WORKS

Linda Wang. [8] developed a deep learning model as COVID-Net which is a Tailored Deep Convolutional Neural Network Design for Detection of COVID-19 Cases from Chest X-Ray Images. COVID-Net is one of the first open source network designs for COVID-19 detection from CXR images at the time of initial release. They investigated how COVID-Net makes predictions using an explain ability method in an attempt to not only gain deeper insights into critical factors associated with COVID cases, which can aid clinicians in improved screening, but also audit COVID-Net in a responsible and transparent manner to validate that it is making decisions based on relevant information from the CXR images. Gao Huang. [9] developed a model using Ensembles o f neural networks which are known to be much more robust and accurate than individual networks. However, training multiple deep networks for model averaging is computationally expensive. He proposed a method to obtain the seemingly contradictory goal of ensembling multiple neural networks at no additional training cost. The resulting technique, which is Snapshot Ensembling, is simple, and surprisingly effective. The series of experiments that our approach is compatible with diverse network architectures and learning tasks. It consistently yields lower error rates than state-of-the-art single models at no additional training cost, and compares favourably with traditional network ensembles. On CIFAR-10 and CIFAR-100 our DenseNet Snapshot Ensembles obtain error rates of 3.4% and 17.4% respectively.

Dilbag Singh. [10] developed a model using convolutional neural networks (CNN) which is used to classify the COVID-19-infected patients as infected (+ve) or not (−ve). Additionally, the initial parameters of CNN are tuned using multi-objective differential evolution (MODE). Extensive experiments are performed by considering the proposed and the competitive machine learning techniques on the chest CT images. Extensive analysis shows that the proposed model can classify the chest CT images at a good accuracy rate. Compared with reverse-transcription polymerase chain reaction (RT-PCR) to chest computed tomography (CT) in which imaging may be a significantly more trustworthy, useful, and rapid technique to classify and evaluate COVID-19, specifically in the epidemic region. However, the chest CT-based COVID-19 classification involves a radiology expert and considerable time, which is valuable when COVID-19 infection is growing at rapid rate

3.PURPOSE

The Existing deep learning algorithmsused to classify computed tomography (CT) are heavy computation-based methodologies and are more focused to a pin point classification of the diseases. In this paper, we aim to develop a robust deep learning algorithm to classify the chest computed tomography (CT) of (COVID-19) among the chest computed tomography (CT) of Viral-Pneumonia with minimal computation and much accurate scores.

4.PROPOSED METHOD

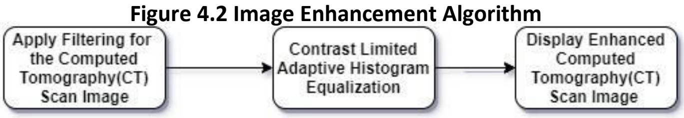
In this section we discuss the proposed method to classify the chest computed tomography (CT) of (COVID-19) among the chest computed tomography (CT) of Viral-Pneumonia. The datasetused contains 1,065 computed tomography (CT) images of pathogen-confirmed 42 (COVID-19) cases (325 images) along with those previously diagnosed with typical 43 viral pneumonia (740 images) .The dataset also contains 1,065 images of infected mask and lung mask images. The Images were passed through a image enhancement algorithm to enhance the local contrasts in the (CT) images. These enhanced (CT) images are passed into a neural network that segments and estimates infected regions in the (CT) Scans. We now pass the estimated infection mask to convolution neural network (CNN) **[14.]** which was previously trained on the Infection Mask images from the Dataset. The CNN would predict if the Original CT image was the chest computed tomography (CT) of (COVID-19) or the chest computed tomography (CT) of Viral-Pneumonia based on its Trainingexperience. The Flowchart in the Figure 4.1 describes an overview of the entire proposed method. The Flowcharts in the subsections Focus on the individual Sub Methods of individual algorithms used in the main method.

4.1 Image Enhancement

Medical images require image enhancement, a category of image processing which provides better visualisation that make diagnostic more accurate **[11]**. The most commonly used method for improving the quality of medical image is Contrast enhancement **[11]**.In this paper we used Contrast Limited Adaptive Histogram Equalisation(CLAHE)**[13]** contrast amplification limiting procedure which enhances the quality of the computed tomography (CT) images. The enhancement through CLAHE is very uniform and it enhances the contrast without increasing noise in the image and also reduces Shadowing effect which is usually seen in regular histogram equalisation (ER) methods. The Resultant computed tomography (CT) images are bright and much effective compared to Original CT Images. The figure 4.2 Flowchart that explains the Image Enhancement Algorithm.

Figure 4.1- FlowChart to describe each steps in the proposed method

Figure 4.2 Image Enhancement Algorithm



4.2 Estimating Infected Region

The Enhanced computed Tomography (CT) is passed through a Snapshot Ensembles which is known to be much robust and accurate compared to an individual network, also this architecture allows to ensembling multiple networks with no additional cost of training and yields lower error rates than state-of-art single models [**9**]. To build a much effective snapshot ensemble requires an aggressive learning rate algorithm, the cosine annealing learning rate [9] where the learning starts form high and is dropped to a minimumbeforebeingincreased to maximumagain.

The network is aimed to predict two segmented

$$\alpha(t) = \frac{\alpha_0}{2}\left(\cos\left(\frac{\pi \operatorname{mod}(t-1, \lceil T/M \rceil)}{\lceil T/M \rceil}\right)+1\right)$$

Figure 4.3- Equation for the Cosine Annealing Learning Rate Schedule [9]

images(lung mask and the infection mask) with one input computed tomography (CT), The need for lung mask is not carried forward in the algorithm but it is used to find the exact area infected in the lung by just overlapping these two images. Once the model is trained, the infected mask and the lung mask of the test image are estimated. The Figure 4.4 contains the flowchart describing the algorithm used for Estimating the Infected region in the Enhanced (CT) images

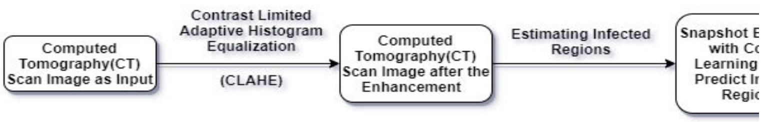
Figure 4.4: Flowchart for Estimating Infected Region

4.3 Classifying TheInfected Region

We Train a Convolution Neural Network (CNN)[**14**] on the pre-Identified Infected Regions in the computed tomography(CT) images present in the Dataset, to classify the Type of Infection. Using the infected region instead of taking the entire CT image drastically reduces the cost of computation needed to classify the computed tomography because this process reduces the need of learning unnecessary features which are otherwise present in the computed tomography (CT) images. The end result from this would be a prediction if the given test image was either computed tomography (CT) image of (COVID-19) patient or a computed tomography (CT) image of viral pneumonia patient.Flowchart in Figure 4.5 briefly describes about the Classification algorithm.

5.RESULTS

The 2019 novel coronavirus (COVID-19) infection has been classified by considering the polymerase chain reaction. The COVID -19 and the viral pneumonia can be identified based on the structure of the infection region present in the computed tomography (CT) images which cannot be distinguished easily with a Human eye. Bilateral multiple lobular and segmental area of consolidation constitute typical findings in the Chest CT



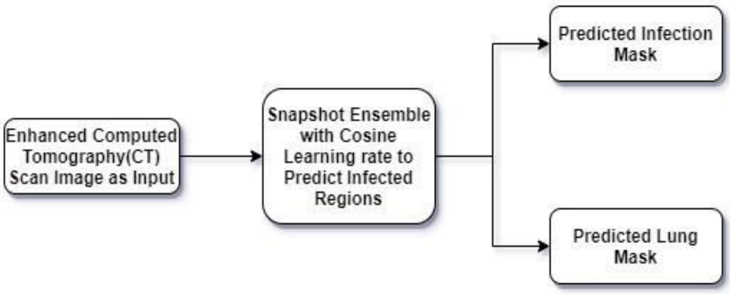
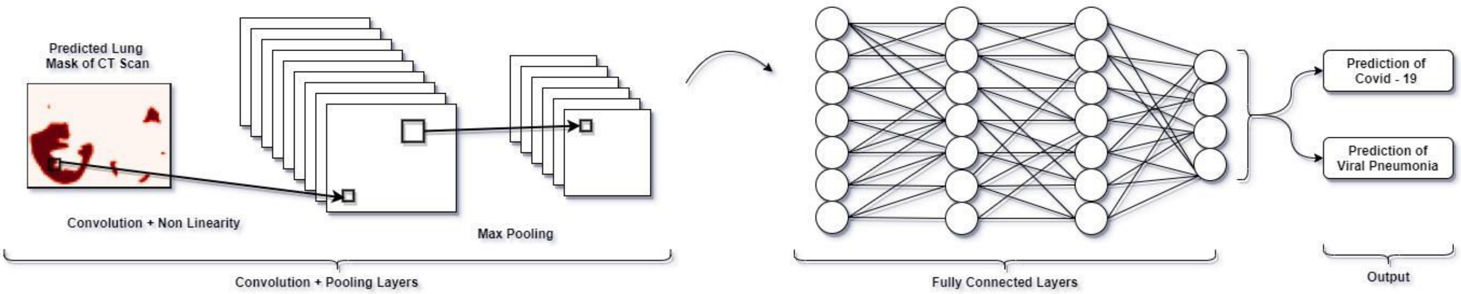
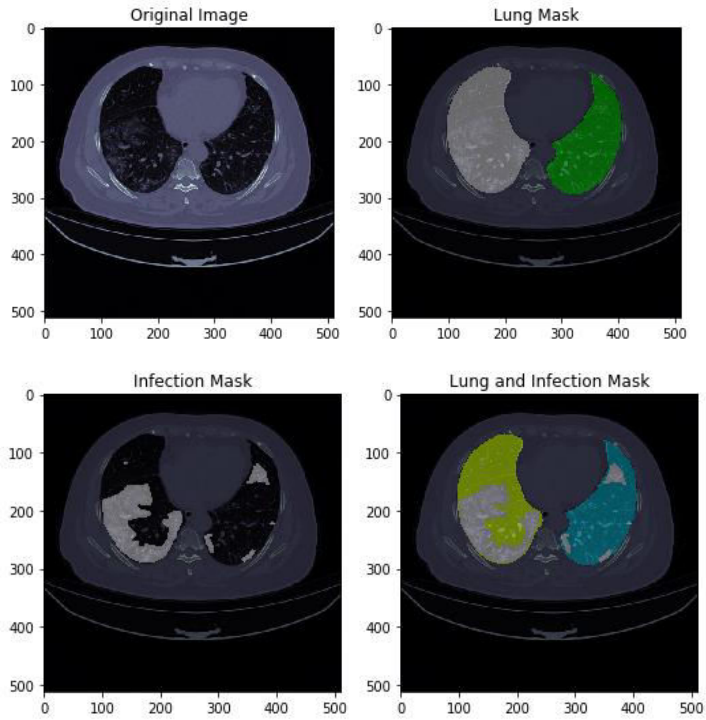


Figure 4.5 Classification algorithm for classifying the predicted Infected region

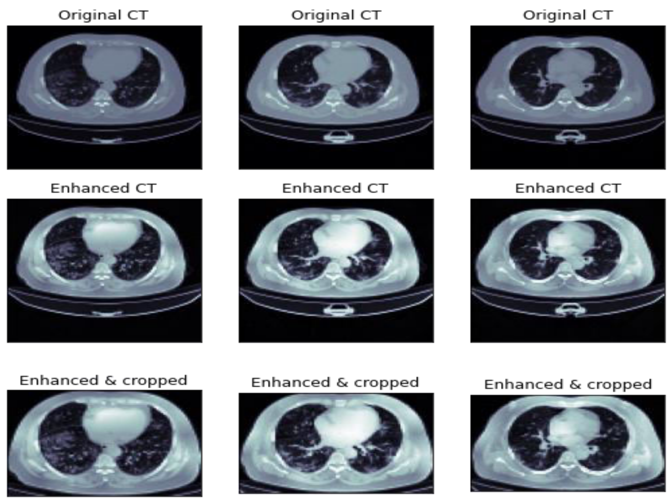




images, in comparison the non-ICU patients show bilateral ground-glass opacity and sub-segmental areas of consolidation in their chest CT images[**12**]. The datasetused contains 1,065 computed tomography (CT) images of pathogen-confirmed 42 (COVID-19) cases (325 images) along with those previously diagnosed with typical 43 viral pneumonia (740 images) .The dataset also contains 1,065 images of infected mask and lung mask images.

Figure 5.1 Sample preview of the images present In the dataset

These computed tomography (CT)images passed through the Contrast Limited Adaptive Histogram Equalisation (CLAHE) [13] image enhancement



algorithm, which increases the contrast and enhances the week portions in the image, since the entire algorithm revolves around estimating infection region, using such enhancement algorithm converts all the low quality features to a understandable level. The Figure 5.2 shows how the regular CT scan images are being enhanced using Contrast Limited Adaptive Histogram Equalisation (CLAHE) algorithm[13]

Figure 5.2 test images of CT scan when subjected to Contrast Limited Adaptive Histogram Equalisation(CLAHE) Image enhancement algorithm

The Enhanced computed Tomography (CT) is passed through a Snapshot Ensembles which is known to be much robust and accurate compared to an individual networks, The figure 5.3 mentions the plots of Dice Coefficient vs Epoch and loss vs Epoch of computed tomography (CT) images.

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The Dice Coefficient **is** used to validate the percentage of similarity in the predicted image compared to the original image, and the loss vs Epoch mentions about the change in the loss as the number of epochs increased.

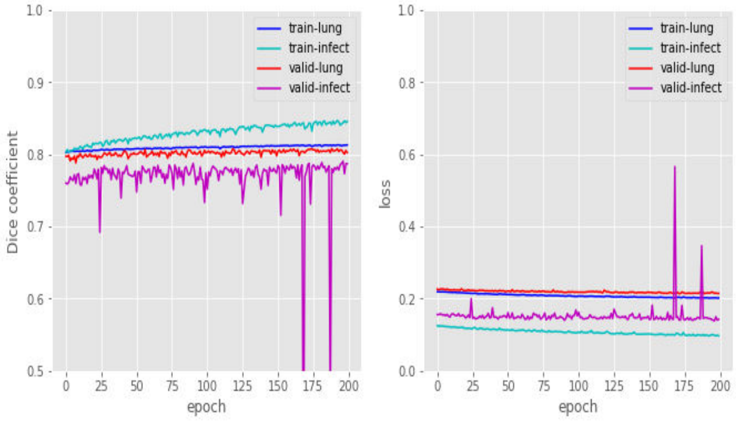

Figure 5.3 plot of Dice Coefficient vs Epoch(left), Loss vs Epoch(Right)

The enhanced images are used further for estimating the

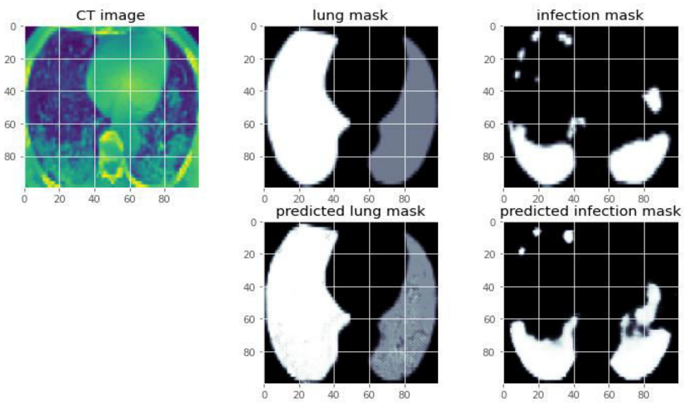

Figure 5.4 Estimating the infected region for a sample test image

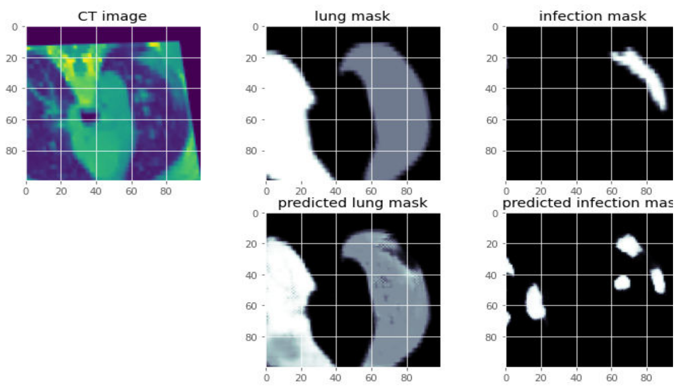

Figure 5.5 Estimating the infected region for a sample test image

infected regions in these images, the figures 5.4,5.5,5.6 explains the estimated infected mask and the lung mask for various Test Images

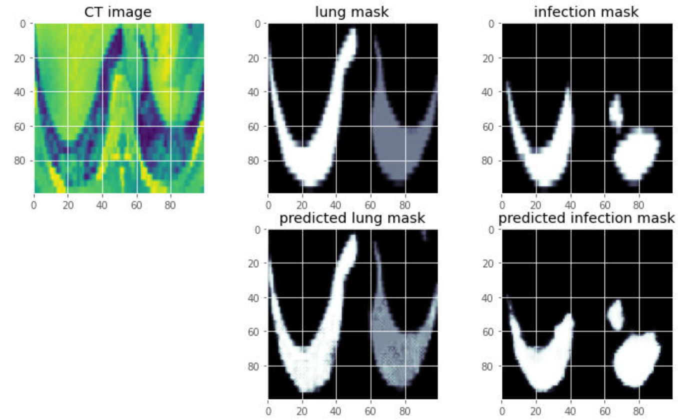

Figure 5.6 Estimating the infected region for a sample test image

The estimated infected region can be overlapped with

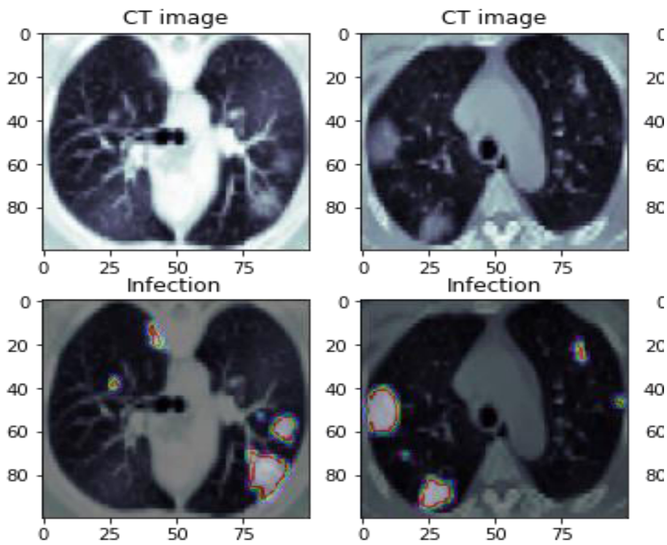

Figure 5.7 The prediction of location of infected region in the CT scan image

the respective CT image to find the exact location of the infection in the images figure 5.7 shows the overcalled infection images

The Predicted Infected regions are classified using the convolution neural network (CNN) which was trained on the pre-identified infected regions present in the dataset. The figure 5.8 explains the graph of the training accuracy vs validation and accuracy and training loss vs validation loss, a better accuracy is seen, because the network was able to pick minute features because the images were more focused on key changes of the infection i.e the image are more inclined towards the infected region structures.

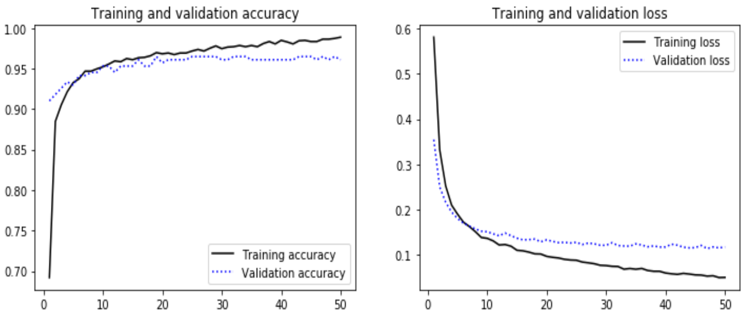

Figure 5.8 plot of training accuracy vs validation accuracy(left), training loss vs validation loss (Right)

The test images are divided into two classes, Class A and Class B. the positive predictive value percentage of viral pneumonia and COVID-19 cases are mentioned in the Table 1calculated for both set A and set B.The score of positive predictive value percentage is considered as a evolution for the Convolution Neural Network which is

Positive Predictive value (%)			
Set A		Set B	
Viral Pneumonia	COVID - 19	Viral Pneumonia	COVID - 19
91.6	94	92.0	93.1

Table 1: Table for Positive predictive value

used for Classifying the predicted infected masks

6. CONCLUSIONS

The Proposed algorithm successfully classified the computed tomography (CT) of the both COVID-19 case and the viral pneumonia case with a better accuracy and the proposed method is unique of its kind in using a estimated region in classifying and this method reduces the complexity of the architecture since, it focuses more on the infected area compared to other competitive algorithms. This method can be further extended to any similar lung diseases and the present proposed method is a binary classification i.e it classifies for viral pneumonia or COIVD-19 cases, which can be extended with a slight modification of the classifying and estimating architectures. This algorithm is robust, and the computation cost still remain same for broader range of classifications and the accuracy can also be increased by using a better estimating algorithm.

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