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COVID-19 Treatment and Segmentation and Classification Using Lung CT Scan Images

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ABSTRACT

Covid-19 is a leading cause of corona virus death in the world. Key to survival of patients is early diagnosis. Computer Aided Diagnosis (CADx) systems can assist radiologists and care providers in reading and analysing Covid-19 CT images to segment, classify, and keep track of nodules for signs of corona virus. In this thesis, we propose a CADx system for this purpose. To predict Covid-19 nodule malignancy, we propose a new deep learning frame work that combines Convolutional Neural Networks (CNN) and Region based segmentation to learn best in-plane and inter-slice visual features for diagnostic nodule classification. Since an odule's volumetric growth and shape variation over a period of time may reveal information regarding the malignancy of nodule, separately, a deep learning based approach is proposed to segment the nodule's shape at two time points from two scans, one year apart. The output of a CNN classifier trained to learn visual appearance of malignant nodules is then combined with the derived measures of shape change and volumetric growth in assigning a probability of malignancy to the nodule. Due to the limited number of available CT scans of benign and malignant nodules in the image database from the National Covid-19 Screening Trial (NLST), we chose to initially train a deep neural network on the larger LUNA16 Challenge database which was built for the purpose of eliminating false positives from detected nodules in thoracic CT scans. Discriminative features that were learned in this application were transferred to predict malignancy. The algorithm for segmenting nodule shapes in serial CT scans utilizes as parse combination of training shapes (SCOTS).

I. INTRODUCTION

Covid-19 is a pair of spongy organs located on both side of the chest. When interpreting the Covid-19 CT scans, it is important to have a solid understanding of Covid-19 structure. A brief overview of Covid-19 anatomy is presented here. Covid-19 s are covered by a tissue layer called pleural, a thin layer of fluid plays as lubricant helping the Covid-19 to move smoothly over the exhalation and in halation. EachCovid-19 can be divided into lobes as shown in each lobe contains its own separate vascular and lymphatic networks. The right Covid-19 is larger because heart is accommodated in the left Covid-19. The left Covid-19 divides into upper and

SEGMENTATION

Segmentation is a fundamental step of most CAD systems. By segmenting the nodule, the shape characteristics can be extracted, helping the radiologists analyse the malignancy as malignant nodules are more speculated. It also provides information on nodule growth over a period of time. However, segmentation is a challenging problem in Covid-19 CT due to the confounding factor that nodules can be attached to the pleural surface with the same Hounsfield Units (HU) or they might have significant overlap with neighbouring vessels.

NODULE DETECTION

To diagnose Covid-19 corona virus, important to detect and interpret the Covid-19 nodules. Fortunately, Low dose CT affords a significant improvement to Covid-19 nodule detection in patients in comparison to chest X-ray so that 20% reduction in mortality is achieved with low-dose CT scans. However, false positivesremainhigh with this modality and a post processing step is needed to reduce false positives. Anoduledetectorsystemtypicallyconsistsoftwosteps

1)Candidatedetectionand
2)Falsepositivereduction.
Incandidatedetection,alargenumberofcandidatesareextractedfromthewholevolumetricCovid-19 CT.Theaimofthissteptoincludeallthenodulesinthelarge set of candidates using a variety of characteristics like intensity, shape features,morphology,etc.Thisstepdetectnoduleswithaveryhighsensitivitywithoutforcingthe system to keep the false positives at a low rate. The features serve to remove false positives and providetheoutputwithahighsensitivityatalowfalsepositiveper scan.

II. METHOD

Pre-processing:

In pre-processing the pattern finding and fitting process for the model, applied several preprocessing methods on the dataset. By using the Hounsfield units (HU) scale by clipping the pixel intensity values of the images to -1,250 as minimum and +250 as maximum, because we were interested in infected regions (+50 to +100 HU) and lung regions (-1,000 to -700 HU)[14,16]. It was only possible to apply the clipping approach on the corona cases Initiative CTs, because the Radiopaedia volumes were already normalized to a grayscale range between 0 and 255. Varying signal intensity ranges of images can drastically influence the fitting process and the resulting performance of segmentation models.

In order to perform preprocessing the salt and pepper noise was added to the scanned image. Because, most of the image will contain amount of noise. By using, median filter the noise is reduced from the scanned image. Now the scanned image was clean data set to perform further operation[15]. Then, image binarization will generate the binary image that has two value one and two it is called the gray scale image.

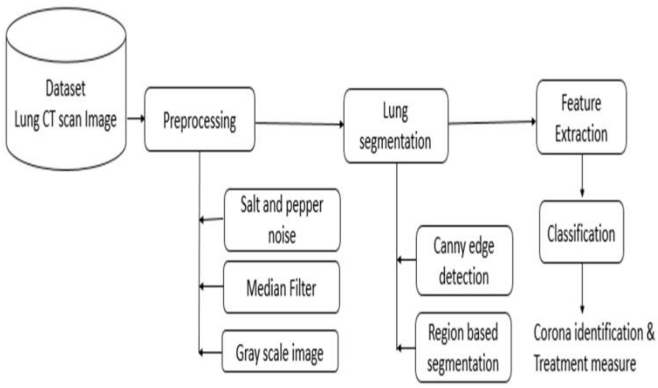

Figure 1. SYSTEM DIAGRAM

Lung segmentation

The segmentation is the process of partitioning the image into segments or constituent objects. Segmentation tasks in COVID-19 application can be divided into two groups: Lung region segmentation and Lung lesion segmentation. During lung region segmentation, the whole lung region is separated from the background. Sharp

Variability of nodules and bring the information from the segmentation process. The adaptive model of the shape which dynamically contributes to the segmentation during surface evolution[18]. Nodule shape in our method are not restricted to a predefined structure; instead the model by approximating the evolving surface by a linear combination of training shapes in a subspace, resulting in a sparse representation of nodule shapes. The sparse shape segmentation represent into a level set segmentation for the framework. In lung segmentation region based segmentation was proposed.

The region based segmentation steps will be followed:

- Threshold segmentation
- Regional Growth Segmentation
- Edge detection segmentation

1. Threshold segmentation

Threshold segmentation is the simplest method of image segmentation and also one of the most common parallel segmentation methods. It is a common segmentation algorithm which directly divides the image gray scale information processing based on the gray value of different targets[17]. Threshold segmentation can be divided into local threshold method and global threshold method. The global threshold method divides the image into two regions of the target and the background by a single threshold. The local threshold method needs to select multiple segmentation thresholds and divides the image into multiple target regions and backgrounds by multiple thresholds. The most commonly used threshold segmentation algorithm is the largest interclass variance method (Otsu), which selects a globally optimal threshold by maximizing the variance between classes.

In addition to this, there are entropy-based threshold segmentation method, minimum error method, and co-occurrence matrix method, moment preserving method, simple statistical method, probability relaxation method, fuzzy set method and threshold methods combined with other methods[19]. The advantage of the threshold method is that the calculation is simple and the operation speed is faster. In particular, when the target and the background have high contrast, the segmentation effect can be obtained. The disadvantage is that it is difficult to obtain accurate results for image segmentation problems where there is no significant gray scale difference or a large overlap of the gray scale values in the image. Since it only takes into account the gray information of the image without considering the spatial information of the image, it is sensitive to noise and grayscale unevenness, leading it often combined with other methods[20].

2. Regional Growth Segmentation

The regional growth method is a typical serial region segmentation algorithm, and its basic idea is to have similar properties of the pixels together to form a region. The method requires first selecting a seed pixel, and then merging the similar pixels around the seed pixel into the region where the seed pixel is located. There are known two seed pixels (marked as gray squares) which are prepared for regional growth[21]. The criterion used here is that if the absolute value of the gray value difference between the pixel and the seed pixel is considered to be less than a certain threshold T, the pixel is included in the region where the seed pixel is located.

3. Edge Detection segmentation

The edge of the object is in the form of discontinuous local features of the image, that is, the most significant part of the image changes in local brightness, such as gray value of the mutation, color mutation, texture changes and so on[15]. The use of discontinuities to detect the edge, so as to achieve the purpose of imagesegmentation. There is always a gray edge between two adjacent regions with different gray values in the images and there is a case where the gray value is not continuous[22]. This discontinuity can often be detected using derivative operations, and derivatives can be calculated using differential operators. Parallel edge detection is often done by means of a spatial domain differential operator to perform image segmentation by convoluting its template and image. Parallel edge detection is generally used as a method of image preprocessing. The widely first-order differential operators are Prewitt operator, Roberts's operator and Sobel operator[23]. The second-order differential operator has nonlinear operators such as Laplacian, Kirsch operator and Wallis operator. In order to perform the edge detection the canny edge detection method is used.

The Canny method principally finds edges wherever the grayscale intensity of the image changes the foremost. These areas are found by decisive gradients of the image. Gradients at every constituent pixel within the smoothened image area determined by applying what's called the Sobel-operator. First step is to approximate the gradient within the x and y direction respectively by applying the kernels. The gradient magnitudes will then be determined as a Euclidean distance measure by applying the law of Pythagoras. However, the edges are generally broad and so do not indicate exactly where the edges are located.

Feature Extraction

A dataset with 100 images is selected, positives and negative classes are balanced. By consequence is necessary to find a transformation from images to Complex Networks. A first proposal is using Frequency Histogram, because it can reduce dimensionality and represent the distribution of pixels. Previously, a transformation of color images is performed to get grayscale images. Later, a proposal using GLCM is done to get neighbourhood features considering texture analysis.

Grey Level Co-Occurrence Matrix (GLCM) algorithm [24] is a second order statistical method use for texture feature extraction. From this matrix, the next features are extracted:

- Contrast : Plevels−1 i,j Pi,j (i − j) 2
- Dissimilarity : Plevels−1 i,j Pi,jki − jk
- Homogeneity : Plevels−1 i,j Pi,j 1+(i−j) 2
- ASM : Plevels−1 i,j P 2 i,j
- Energy : p (ASM)
- Correlation : Plevels−1 i,j Pi,j (i−μi)(j−μj) sqrt(σ 2 i σ 2 j)

Histogram frequency were calculated to a lower dimensionality representation the statistical features were calculated, mean, standard deviation, kurtosis and skew. This histogram is considering the three channels of classical RGB image representation. Using this to find a visual difference between positive and negative cases. Using Frequency Histogram and GLCM is possible to notice that Complex Networks building is possible using euclidean distance[25]. Besides, the representation of Complex Network through adjacency matrices presents reticular patterns. This patterns are different, positive cases presents a distribution of further or higher distances between the nodes/elements than negative ones. By contrast, negatives samples presents only a few link with high distances.

Classification

Classification is often termed as Computer-Aided Diagnosis (CAD).Classification plays a significant role in medical image processing. During the classification processing phase, one or even more images are taken as input samples, and a single diagnosis factor is generated as an output which classifies the image.The neural network architecture and its hyper parameters are one of the key parts in a medical image segmentation pipeline. In this work, implemented the standard 3D UNet as architecture in order to avoid unnecessary parameter increase by more complex architectures like the residual variant of the 3D U-Net. It allows for flexibility in balancing the false positive rate (FP) and false negative (FN) rate[26]. The crossentropy is a commonly used loss function in machine learning and calculates the total entropy between the predicted and true distribution. The detection procedure involves 97 chest CT-scanned images, two deep-neural hidden layers. Spatial Configuration-Net (SCN) architecture was used to combine accurate response with landmark localization. Experimental evaluation of 3D image datasets using CNN and the SCN architecture provides higher accuracy. The proposed a CNN of 16 layers only to detect COVID-19 using both X-ray and CT scans and reported good performance.

Region based segmentation algorithm

The segmentation algorithm will be segmenting the lung to separate two homogeneous regions while forcing the segmentation to be consistent with the training shapes. Add another term to the surface evolution alongside with original active contour equation helps guide the surface not only by low-level intensity statistics, but also by high level shape prior information[28]. Specifically, in each step of surface evolution, it moves in a direction to optimize the function and concurrency. The algorithm moves along aspecificdimensionandfindstheoptimumvalueforthatspecificentry.

$D=[\phi_1|\phi_2|\ldots|\phi_n]$,$\mathbf{x}=[x_1,x_2,\ldots x_n]$,

$D^{(-i)}=[\phi_1|\ldots|\phi_{i-1}|\phi_{i+1}|\ldots|\phi_n]$,

$\mathbf{x}^{(-i)}=[x_1,\ldots,x_{i-1},x_{i+1},\ldots x_n]$.

The algorithm consists of two nested loop. In the outer loop the segmenting lungs gets updated in the direction of a linear combination of Chan-Vese and sparse shape prior terms. The inner loop refines the updated shape and brings it into the vaild shape spave. The energy function as the sum of the Chan-Vese function and computed sparse linear approximation.

$E(\varphi(t),\mathbf{x}(t))=E_{cv}(\varphi(t))+E_{sp}(\varphi(t),\mathbf{x}(t))$

Classification algorithm

Convolutional Neural Networks come under the subdomain of Machine Learning which is Deep Learning. Algorithms under Deep Learning process information the same way the human brain does, but obviously on a very small scale, since our brain is too complex (our brain has around 86 billion neurons).

Different pooling operations utilized to further reduce the dimensionality of feature maps. A stride of size 3 is adopted here, with pooling operations, to further reduce the dimension of the resulting feature maps taking into consideration the fact that there is redundant information in images and neglecting a row and a column after each pooling window is not causing a massive information loss[29]. Difference between pooling of size 3-by-3 with stride 2 versus pooling of size 2-by-2 with stride 3 and conclude that we are not losing much information while reducing the size of the image/feature map further.

Steps

Step 1 : Choose a Dataset
Choose a dataset of your interest or you can also create your own image dataset for solving your own image classification problem

Step 2 : Prepare Dataset for Training
Preparing our dataset for training will involve assigning paths and creating categories (labels), resizing our images

Step 3 : Create Training Data
Training is an array that will contain image pixel values and the index at which the image in the CATEGORIES list.

Step 4 : Shuffle the Dataset

Step 5 : Assigning Labels and Features
This shape of both the lists will be used in Classification using the NEURAL NETWORKS.

Step 6 : Normalising X and converting labels to categorical data

Step 7 : Split X and Y for use in CNN

Step 8 : Define, compile and train the CNN Model

Step 9 : Accuracy and Score of model

Pre-processing and Training the model (CNN)

The database is Pre-processed such as Image reshaping, resizing and Conversion to an array form. Similar processing is also done on the test image. A database consisting of about 32000 Different plant species is obtained, out of which any image can be used as a test image for the software[30]. The train Database is used to train the model (CNN) so that it can identify the test image and the disease it has .CNN has different Layers that are Dense, Dropout, Activation, Flatten,Convolution2D, MaxPooling2D. After the model is trained successfully, the software can identify the disease if the plant species is contained in the database. After successful Training and pre-processing, comparison of the test image and trained model takes place to predict the disease.

Algorithm 2 Training process of wCNN (wCNN=wCPNN+FCNN)

Input:

train_x, ***train_y***, ***test_x*** and ***test_y*** are set same as the pseudocode of CNN

Output:

$wc^l_{ij}, bc^l_j, ac^l_j$: weights and bias of wCPNN ($l = 2, 4$, wCPNN have 5 layers)

w_{jk}, b_k : weights and bias of FCNN (FCNN have 2 layers)

Required parameters:

max_time and ***target_error*** are set same as the pseudocode of CNN

η_wCPNN,: learning rate of wCPNN

Initialization work:

t=1 and $loss(1) = 1$ are set same as the pseudocode of CNN

$wc^l_{ij}, ac^l_j, bc^l_j, w_{jk}, b_k$: weights and bias of wCNN are set as random number.

Begin:

Set the required parameters and complete the initialization work

while $t < max\_time$ and $loss(t) > target\_error$

  for all *trainingSet*:

    train_p (prediction of label) is calculated according to ***train_x*** and forward calculation formula 29-31 and 4-9.

  end for

  $loss(t)$ is re-calculated as $loss(t) = \frac{1}{2}\sum_{n=1}^{N}(train\_p(n) - train\_y(n))^2$, N is the total number of *trainingSet*.

  $\Delta w^{-1}_{ij}, \Delta b^{-1}_j$ and $\Delta w^l, \Delta ac^l, \Delta bc^l$ are calculated according to the formula 22-23 and 34-36

  $w^{-1}_{ij}(t), b^{-1}_j(t)$ and $w^l(t), ac^l(t), bc^l(t)$ are adjusted according to the formula 37-41

  t++

end while

End

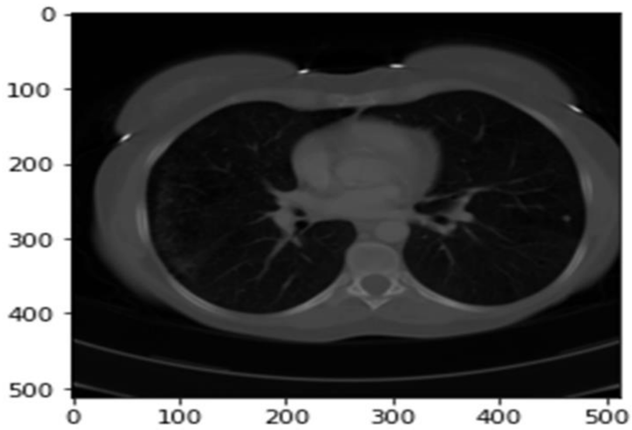

Figure 2. INPUT IMAGE

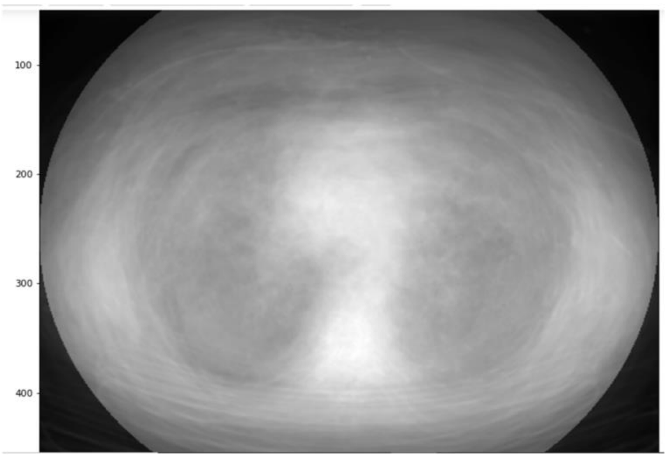

Figure 3. NOISE ADDED IMAGE

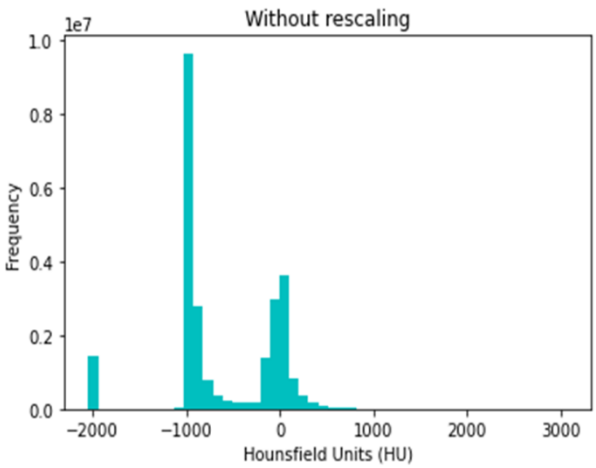

Figure 4. PREPROCESSING PLOT

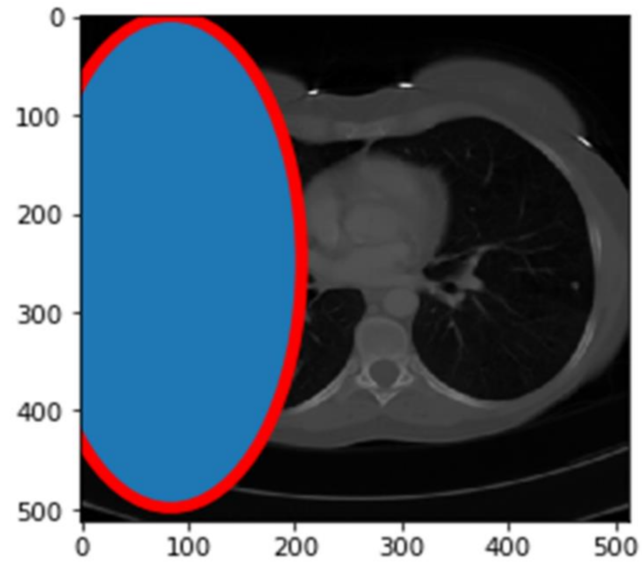

Figure 5. SEGMENATION IMAGE

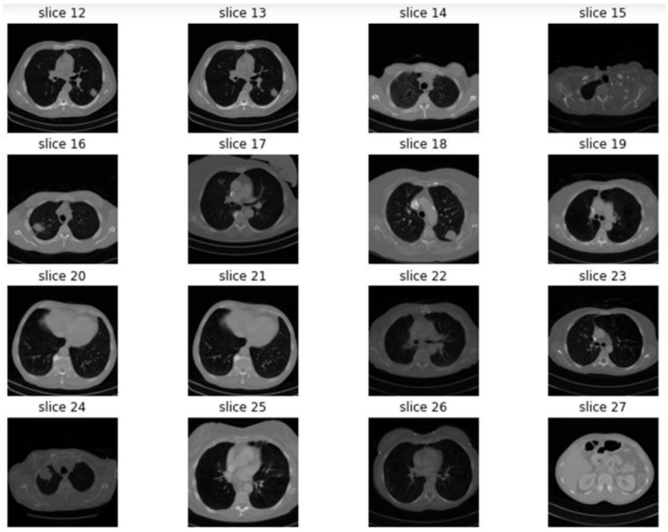

Figure 6. CLASSIFICATION

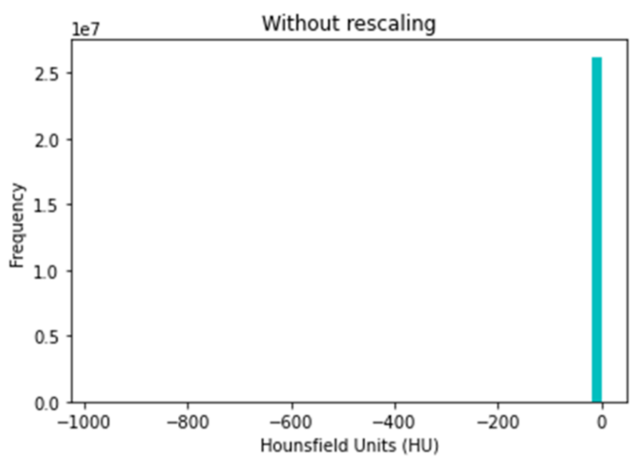

Figure 7. ACCURACY LEVEL

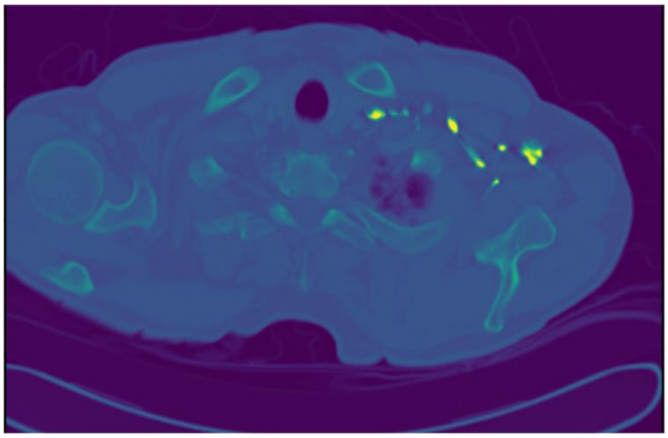

Figure 8. FINAL OUTPUT

III. RESULTS AND DISCUSSION

Our system provides the feasible solution for detection of COVID-19 in lung CT scan image. In this work, we present the region based algorithm and CNN algorithm that can reduce both false positive and false negative by using pre-processing and training model. Furthermore, we were able to outperform current state-of-the-art the segmentation approach for the lungs and COVID-19 infected regions. Real-time data has been used for this analysis and not the conventional data because the data validity of real time data highly depends on the time and its response time requirements come from the external world. The COVID-19 have brought about many new problems for humanity solved with Deep Learning, we hope to provide a realistic solution to detection of COVID-19 in the lung CT scan image. Our system not only detects the COVID-19, but also provides a level of the affection and suggest the medicine for the patients.

IV. CONCLUSION

Two Machine Learning models were used but in future Deep Learning models or hybrid two or models can be used to forecast the further spread of the virus. Real-time data has been used for this analysis and not the conventional data because the data validity of real time data highly depends on the time and its response time requirements come from the external world. Although the real time data can be relaxed in a few cases unlike the conventional data which needs to satisfy every case.

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