Stroke detection and segmentation in CT images using Convolutional Neural Networks and Active Contour Geodesic Method

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Abstract: A challenge in computer vision is the aid to medical diagnosis; a standard process in these systems is the segmentation of diseases in medical images, such as computed tomography (CT) scans. Stroke stands out in several countries, being one of the leading causes of death globally. The creation of artificial intelligence systems can aid in diagnosing diseases using CT scans to segment and extract useful information. In this work, we propose a solution for the segmentation of CT images using Convolutional Neural Networks and techniques of Digital Image Processing called Geodesic Active Contour Method, aiming to improve the aid in medical diagnosis. We use Detectron2 as a neural network to perform the primary segmentation of the stroke. Then, a post-processing of the network outputs is performed using the Geodesic Active Contour method. We obtained outstanding results in segmentation with this methodology, such as accuracy reaching above 99%. Our method aims to bring a refined solution for the segmentation of medical exam images using deep learning and computer vision techniques.

Keywords:
Detectron2, Stroke, Detection and Segmentation, Geodesic Active Contour

1. INTRODUCTION

Stroke is one of the most common health problems worldwide. It is caused most often by diseases associated with factors such as obesity, hypertension, and diabetes (Sirdani et al., 2021). In the United States, stroke was the fifth most frequent cause of death in the country during the year 2020 (Murphy et al., 2021).

There are two main types of stroke, ischemic and hemorrhagic. Ischemic stroke occurs due to the blockage of cerebral vessels, preventing vascular circulation in the area; this type of stroke is responsible for about 80% of cases, being the most common among them (Tintinalli, 2015; Marx et al., 2013). A rupture of a blood vessel causes hemorrhagic stroke, causing blood to leak into the brain - within the tissue or in the region between the brain and the meninges - and is responsible for about 20% of stroke cases (Tintinalli, 2015; Marx et al., 2013). Furthermore, hemorrhagic stroke has a much higher mortality rate when compared to ischemic stroke, and this is the primary type of stroke caused by high blood pressure (Corrigan, 2013).

In addition to the high mortality rate, stroke has an increased risk of causing loss of movement in some areas of the body, depending on the affected area of the brain (Langhorne et al., 2011).

A computed tomography (CT) is one of the techniques used to analyze stroke cases, which has satisfactorily helped the medical diagnosis. This exam can also allow the early identification of signs of possible complications for the patient, such as heart attack (Lövblad and Baird, 2010).

To perform a CT scan analysis, a radiologist needs to manually analyze and segment the area of interest (Hu et al., 2020). To accelerate medical diagnosis, are being created different technologies to perform the segmentation of the stroke area in an automatic way, using Digital Image Processing (DIP) (Sarmento et al., 2019) and Deep Learning techniques such as Deep Neural Networks (DNN) (Feng et al., 2018).

The Geodesic active contour is a widely used technique in the image segmentation process for the most diverse purposes, and it has obtained good results in general (Ma et al., 2021). Gui et al. (2021) applied this technique to perform lumen segmentation in intravascular optical coherence tomography and obtained satisfactory results in the being evaluated metrics, such as an average Dice coefficient of 93.6%.

Based on the superb results obtained through the use of the Geodesic active contour, this study aims to present a new method of segmentation of strokes, using this technique combined with a deep learning method.

The sections covered in this work are organized in the following sequence. In Section 2, we discuss some existing related works that involve the segmentation of medical images. Section 3 presents the dataset used and the technologies and techniques applied in this study. Section 4 describes the steps performed to segment a stroke automatically. Section 5 discusses the results obtained after applying the techniques proposed in this study.

2. RELATED WORKS

This section will present some works that perform a segmentation step in medical image analysis, focusing on DIP, machine learning, and deep learning.

2.1 Segmentation using DIP and Machine Learning

Computed-aided diagnosis (CAD) systems can help improve medical exam accuracy (Cicerone and Camp Jr, 2019). Based on this, Ali et al. (2021) proposed a method using image processing to segment hemorrhagic strokes with five different techniques, i) threshold, which consists of histograms analysis, ii) FCM, and iii) K-Means, in which both use clusters to identify the stroke, iv) Region Growing, using pixels similarity, and v) Watershed, finding mathematical morphology. The proposed method achieved great results. However, the techniques have problems with image pre-processing, and the methods are not automatic, requiring human adjustments, like image resizing and parameter adjustments.

2.2 Segmentation using Deep Learning

Most papers on hemorrhagic stroke segmentation currently use deep learning as the main method to perform this task due to its efficiency and processing time.

Abramova et al. (2021) proposed a method to segment hemorrhagic stokes with a deep learning method based on a U-Net architecture aided by squeeze-and-excitation block. This block has an architecture made to improve the power of a network and consists of a convolutional block as input, and each channel is boxed up to a single value using average pooling. After this, the network uses a dense layer with an activation function (ReLU) to add non-linearity and reduce the output channel complexity. Then, one more dense layer with a sigmoid cause a smooth gating function. The authors used a 76-case dataset. They concluded that including a symmetric modality helped to improve the metrics, obtaining a mean Dice of 0.862 ± 0.074. Although these results could not be acceptable for clinical use because the authors took as reference just one metric, the mean Dice, which can mask some errors.

Still, on the topic of using deep learning, Han et al. (2020) proposed a method to extract deep features of two databases: i)lungs image database and ii) stroke image database. At first, the images were classified to discard those which did not have any region of interest (RoI). After that, the Detectron2 network was used to segment the RoI from the images classified as applicable. Then, aiming to compare the results with other works, three fine-tuning methods (parzen window, K-means clustering, and region growth) were applied to improve the metrics. And finally, five metrics were compared: Accuracy, Dice coefficient, Sensitivity, Specificity, and Time. This work obtained excellent results with that method, both metrics and execution time.

With the same purpose, Hu et al. (2020) proposed an automatic lung segmentation method using Mask R-CNN network and Machine Learning models. This method applied transfer learning, dilation, and erosion after Mask R-CNN segmentation. This approach had excellent results, even compared to deep learning methods.

3. MATERIAL AND METHODS

In this section, we will present the dataset and the methods and technologies used to perform the segmentation of the stroke area.

3.1 Dataset

The stroke CT image dataset consists of 182 images in Digital Imaging and Communications in Medicine (DICOM) format, which were converted to Joint Photographic Group (JPG). The dataset has different patients who had a stroke, with 100 images of hemorrhagic strokes, which we will use in this study, and 82 of ischemic strokes, which we will not use for this specific study. Each image has a ground truth (GT) of the stroke regions.

3.2 Hardware configurations

The experiments with the Detectron2 models were performed in the following hardware and software configurations: the GPU used is an RTX 1650, the CPU model is a Ryzen 7 3600 and the hardware also has 8GB of RAM. The operating system used is Ubuntu 20.04 LTS.

3.3 Detectron2

Detectron2 is a successor to Detectron and a derivative of MASK-RCNN, developed by Facebook AI's Research (FAIR). It is a platform that implements keypoint detection and labels detection effectively, delimiting them with a colored mask (Divya and Peter, 2021). In terms of segmentation and detection, it is considered state of the art. In addition to MASK-RCNN, it implements TensorMask, Faster R-CNN, DensePose, and other methods of detecting objects in images and videos (Yagüe et al., 2022). Supporting, in terms of segmentation, three different methods:

(1) *Semantic segmentation*
(2) *Instance segmentation*
(3) *Panoptic segmentation*

The instance segmentation is the method used in the experiments of this study. To train the network Detectron2, we used the GTs present in the dataset. Then, the network could learn to segment the region of interest (ROI) correctly. The outputs, after training, are given by the properly labeled image with the colored mask in the ROI and the respective binarized image showing the labeled area.

3.4 Geodesic Active Contour Method

The first occurrence of the term “geodesic active contour” was the approach formulated by Caselles et al. (1997) in which it was shown that level set functions can manipulate different topologies by minimizing geodesic curves (Caselles et al., 1997). Equation 1 shows this process.

$$\frac{\partial u}{\partial t} = g(I)\left|\nabla u\right|\left(div\left(\frac{\nabla u}{\left|\nabla u\right|}\right)+v\right)+\nabla g(I)\nabla u+g(I)v\left|\nabla u\right| \tag{1}$$

When observing this partial differential equation (PDE) three components responsible for the execution and correction of the method are observed:

1. In the first component of this PDE, we can observe the smoothing force that aims to approach the contour of the level set to a geodesic curve.
2. The second part of the equation refers to the force of attraction, whose function is to attract the contour of the curve to the vector normal to it (Medeiros et al., 2019).
3. However, this force may not be strong enough to make the curve evolve, and therefore, in the third installment, it is necessary to use the balloon force to attract the curve even when a homogeneous region induces a very low gradient (Medeiros et al., 2019).

Even though it is a robust approach, the calculation necessary for its execution is extremely expensive, making convergence slow and dependent on the PDE calculation.

3.5 Metrics

The evaluation metrics measure the efficiency of many machines and deep learning methods. knowing that, the following section will show the metrics used to evaluate the proposed method and compare it with the state of art

Accuracy: Accuracy (Acc) can be described as the part of predictions in which are correct predictions. In this paper, it represents the fraction of correctly segmented pixels compared to GT. The Equation 2 corresponds to the calculation of this metric, in which TN corresponds to true negatives, FP to false positives, FN false negatives, and TP true positives.

$$Acc = \frac{TP+TN}{TP+TN+FP+FN} \tag{2}$$

Sensitivity: Sensitivity (Sen) can be described as the relationship between the number of pixels correctly segmented and all pixels present in the region of interest, which is represented in Equation 3. TP corresponds to true positives and FP to false positives. In this study, this metric applies to the segmentation rate whose stroke was correctly segmented over the actual area of the stroke in pixels.

$$Sen = \frac{TP}{TP+FN} \tag{3}$$

Specificity: Specificity (Spe), shown in Equation 4, is used to indicate the relationship between the number of pixels correctly segmented and all the pixels in the background region. This metric corresponds to what the algorithm correctly segmented the stroke in reference to the image background in this article. In Equation 4, TN represents true negatives while FP is the number of false positive segmented pixels.

$$Spe = \frac{TN}{TN+FP} \tag{4}$$

Dice coefficient: The Dice coefficient is a statistic metric to measure the similarity between two samples. In this study, this metric verifies the similarity between the algorithm’s output already segmented and the GT made by a specialist doctor. Equation 5 shows how the calculation is done.

$$Dice = \frac{2\times TP}{2\times TP+FP+FN} \tag{5}$$

4. METHODOLOGY

In this section, the methodology used in this work to perform the stroke segmentation will be detailed, having been divided into three stages: training stage, detection stage, and segmentation stage.

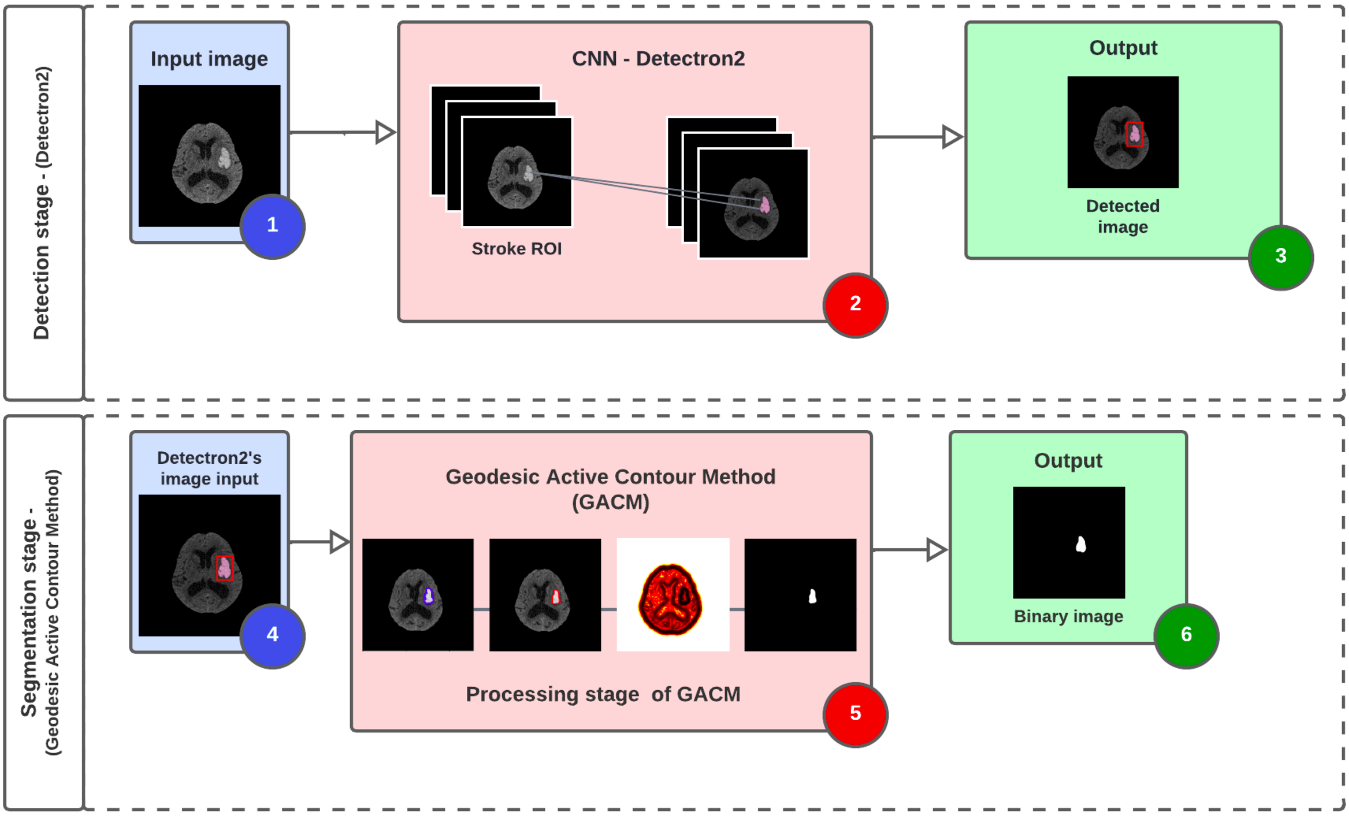
4.1 Training Stage

In this step, the Convolutional Neural Network(CNN) training process was performed, which, as previously mentioned, we used the Detectron2 network, presented in the Section 3.3. The model training consists of using the dataset, described in the Section 3.1, in which was divided in 80% of the images being used for training and 20% for testing. We executed 2500 iterations to train the model to generate the hemorrhagic stroke detection model. In this step, the input of the dataset containing the training images is used, then the CNN Detectron2 network processes the input images, generating an output model. Finally, we have a trained model to detect stroke regions.

4.2 Detection Stage

The stroke detection process begins with the input image, as we can see in Figure 1-Step 1. The second step includes, the use of trained Detectron2 model in this input image. The Detectron2 model is used to find the stroke ROI, detecting the pixels that are within the ROI and those that are not to delimit the detected area. Finally, in Step 3, the output of Detectron2 is displayed after its detection, generating an image with a bounding box delimiting the detected region.

Figure 1. Methodology steps to automatically perform a segmentation of a hemorrhagic stroke region, divided in two stages: Detection and Segmentation.



4.3 Segmentation Stage

In this stage, the Geodesic Active Contour method (GACM) was implemented to segment the hemorrhagic stroke region. Figure 1 demonstrates this process, in which we can observe that the GACM model was loaded using the Detectron2 output, thus performing the fine tuning of the neural network. Figure 1-Step 5 shows the image processing through GACM, having an image with the initial contour, one with the geodesic curve with configured background, and one with a gradient with derivative, displaying a binary mask as output. The result of applying this method is shown in Figure 1-Step 6.

5. RESULTS

In this section, the results of this study are presented. The results are divided into two stages. Table 1 presents the results of the first stage, the detection and segmentation. This stage is where the results from the two models (Detectron2 and Detectron+Geodesic) are discussed. In the second stage, the results obtained with the proposed method are compared with state of art; this comparison can be seen in the Table 2

First stage of results

In this results stage, Table 1 presents the detection results generated by the Detectron2 model, followed by the model generated based on fine-tuning for the segmentation of the stroke region.

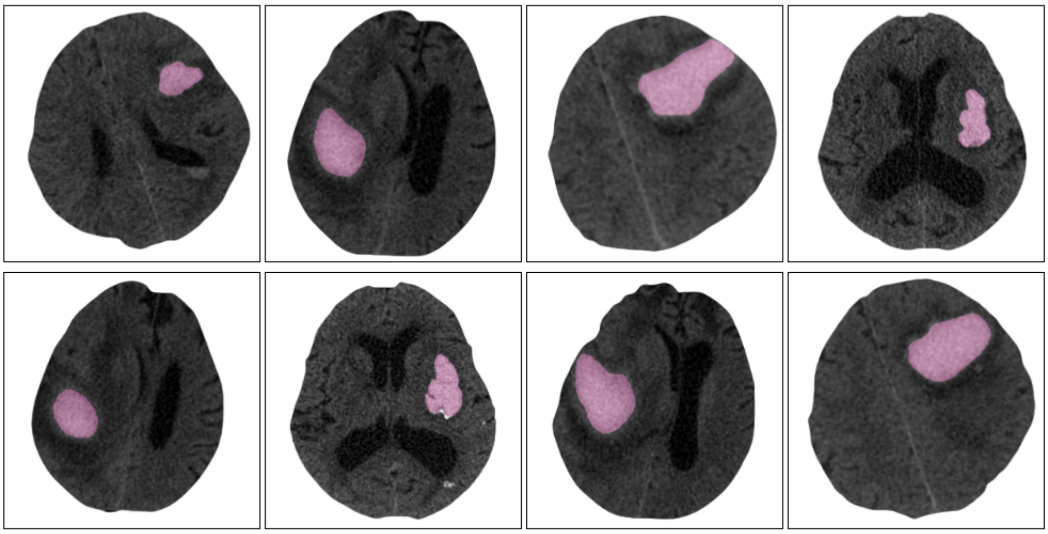
In Table 1, we can note that the values obtained by Detectron2 present similar values, both for detection and for segmentation, using fine-tuning generated by the Detectron+Geodesic model. Both methods achieved 99.85% of accuracy, which shows the ability of the Detectron2 network to identify the stroke region through a bounding box, detecting the existing pixels in the CT image belonging to the hemorrhagic stroke. The model also achieved excellent results in identifying non-stroke regions, as shown by the specificity metric (Spe) with 99.96% based on false positives.

The model based on fine-tuning is also presented in the Table 1 (Detectron+Geodesic), where the results of segmentation of the hemorrhagic stroke region are presented. In this segmentation process, the model obtained excellent results, with an accuracy of 99.85% with a standard deviation of 0.05%, demonstrating the effectiveness of the

Table 1. Results of Detectron2 and Detectron2 convolutional models and fine-tuning model using geodesic active contour for hemorrhagic stroke segmentation.

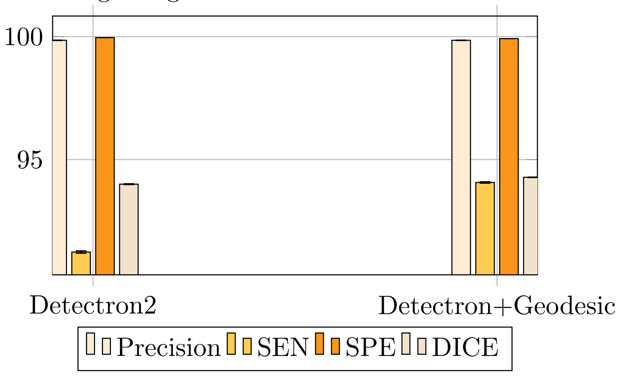
	Acc	Sen	Spe	Dice
Detectron2	**99.85 $\pm$ 0.06**	91.24 $\pm$ 5.03	**99.96 $\pm$ 0.30**	94.00 $\pm$ 2.55
Detectron2+Geodesic	**99.85$\pm$ 0.05**	**94.07 $\pm$ 3.60**	**99.92 $\pm$ 0.70**	**94.28 $\pm$ 1.85**

Figure 2. Segmentation results using Detectron2+Geodesic.



model in segmenting contour regions of the hemorrhagic stroke. This was due to the process of using the fine-tuning method using the geodesic, which, from the detection and initialized based on the region of interest, the delineation of different contours of the hemorrhagic stroke. These superb results are shown by the different metrics in the Table 1; (Sen), (Spe), and (Dice) obtained results above 94%. The metric (Spe) obtained 99.92%, demonstrating the efficiency of the model in finding different contours belonging to the stroke region. The most improved metric was (Sen), in which can be observed in Figure 3.

Figure 3. Chart of results compared with and without fine-tuning using the Geodesic method.



Then, the model of this study proposed, based on deep learning for detection and segmentation of hemorrhagic stroke regions, presented different results, obtaining efficiency based on studies found in the literature. Figure 5 visually shows the segmentation result using the Detectron2+Geodesic model, the method proposed by this study. That can be considered an innovative method using geodesic in the segmentation step, post-processing of the network, which receives the result, generating a new result for segmentation.

The next stage of results presents comparisons that approach such studies based on deep learning.

Comparison with state of the art

In this step, we compare the results of works found in the literature, in which have different approaches based on deep learning using fine-tuning. Table 2 presents the Method proposed by this work in comparison with different convolutional models using fine-tuning found in the literature.

The proposed method presented in Table 2 represents the detection and segmentation model (Detectron2+Geodesic). In this model, it is possible to identify the robustness of the model compared to works found in the literature. Both works listed in Table 2 present studies with the same database and use deep learning to detect hemorrhagic stroke regions. Also, in both works, the authors use fine-tuning to segment the stroke.

Thus, the results of the proposed model (Detectron2 + Geodesic) surpass state of the art in the Accuracy metric (Acc), obtaining 99.85% against 97.68% in its best model (Mask+Kmeans) proposed by Hu et al. (2020). Furthermore, we can observe a difference of 13% in the worst case obtained by the method (Mask+Bayes) of Hu et al. (2020). These comparative studies are renowned and consolidated works in the literature, in which they are presented in different methodologies.

The model presented by Han et al. (2020) (Detectron-fu) achieved the second best result for the problem of detection and segmentation of hemorrhagic stroke, obtaining similar and equivalent metrics in the metric of (Sen) 94.07% against 96.74%, (Spe) 99.92% against 99.92%, being surpassed in the metric (Dice) with 94.28% against 99.02%. These results show that both models could identify less accurate contours in regions that delimited the barrier of ions belonging to the blood-unidentified pixel in the CT image. This approach proposes the identification of different shades of gray in the color of the CT image, and the proposed model is effective in distinguishing how the existing pixel in that region is identified as blood resulting from the existing hemorrhagic stroke.

Then, to compare different works using deep learning and fine-tuning, this study proposes an effective model

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Table 2. Results compared with state of the art.

	Acc	Sen	Spe	Dice
Proposed Method	**99.85± 0.05**	94.07 ± 3.60	**99.92 ± 0.70**	94.28 ± 1.85
Detectron-fu (Han et al., 2020)	97.01± 1.25	**96.74 ± 2.78**	99.45 ± 0.49	**99.02 ± 0.60**
Mask R-CNN (Hu et al., 2020)	89.96 ± 4.38	87.72 ± 16.82	86.70 ± 6.12 ±	76.81 ± 16.90
Mask + Bayes (Hu et al., 2020)	86.42 ± 11.11	91.06 ± 14.66	78.05 ± 17.25	76.10 ± 16.49
Mask + SVM (Hu et al., 2020)	95.78 ± 2.62	96.69 ± 10.24	92.18± 4.87 ±	86.05 ± 11.21
Mask + K-means (Hu et al., 2020)	97.68 ± 3.42	96.58 ± 8.58	97.11 ± 3.65 ±	97.33 ± 3.24
Mask + EM (Hu et al., 2020)	97.28 ± 3.85	95.86 ± 8.67	96.42 ± 4.49 ±	87.63 ± 9.39

for overcoming state of the art, mainly comparisons with renowned works found in the literature.

6. CONCLUSION AND FUTURE WORKS

This study proposes an approach based on deep learning with fine-tuning for the detection and segmentation of regions of hemorrhagic stroke in CT images. In this work, the Detectron2 network is used for the detection of hemorrhagic stroke, and the use of the method geodesic active contour as fine-tuning for stroke region segmentation. The Detectron2+Geodesic model obtained 99.85% of accuracy, surpassing works found in the literature, thus obtaining different metric values for the detection problem, equivalent to state of the art, and obtaining great efficiency results in the problem of medical images through computer models of artificial intelligence.

For future work, it is expected to use different bases of hemorrhagic stroke, as well as different problems of detection and segmentation of CT images, such as; melanomas, lung nodules, and brain tumors.

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