Assisting Retina Image Diagnosis with DNN-based Object Detection

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Motivation

Diabetic Retinopathy is a typical retinal disease that affects tons of people, several works have been done on automatic diagnosis using machine learning based methods. [1]
However, after discussed with the cooperating physician, we found that "currently a more helpful task of AI for doctors is not diagnosing the disease, but discovering symptoms that assist them to diagnose".
Therefore, we aimed to find a DNN-based object detection method that can detect symptoms on retina images to serve as the first-stage diagnosis of Diabetic Retinopathy(Fig.1).

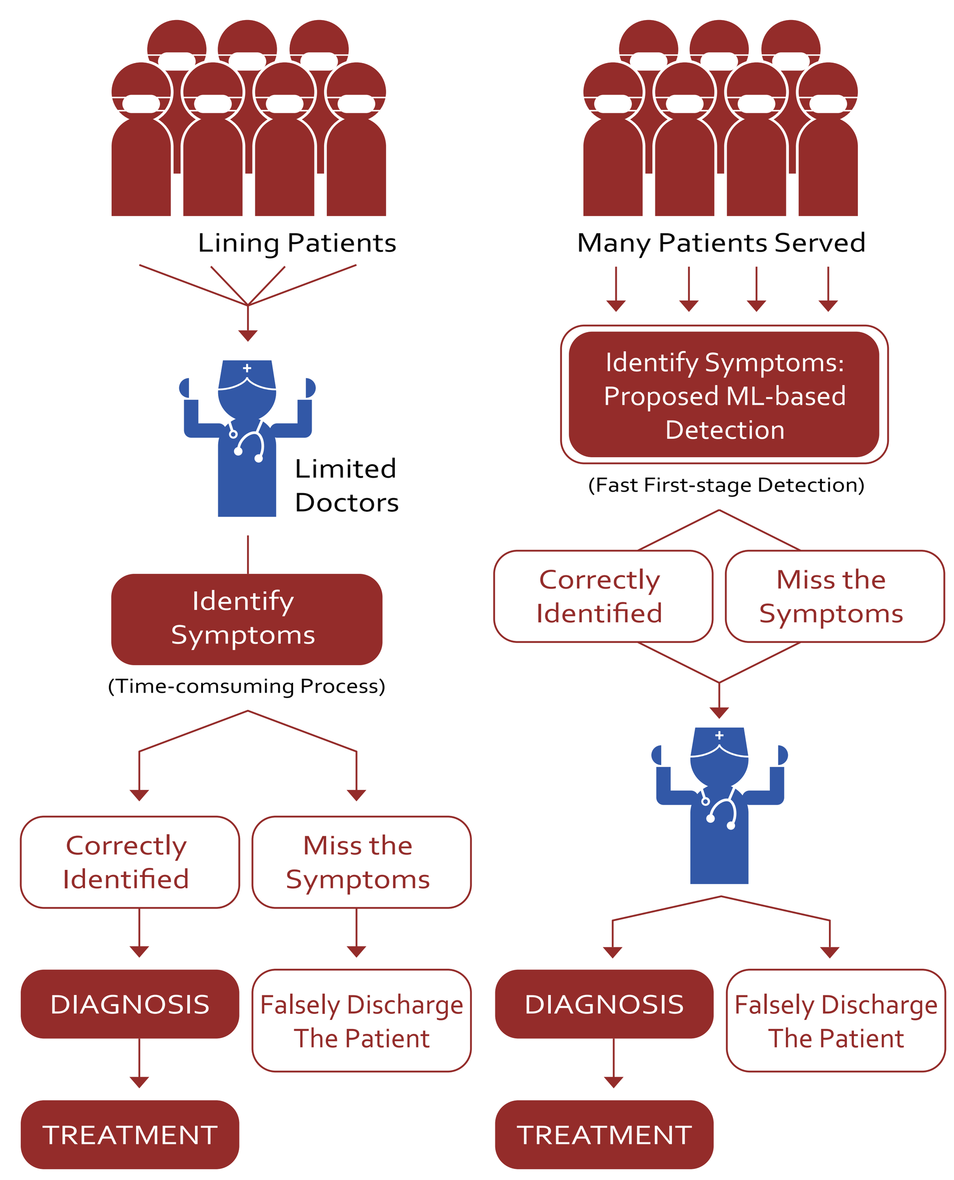

Fig.1 Comparison between the traditional diagnosis framework and our proposed framework. With ML-based symptom detection, the workload of limited physician can be reduced and more patients can be served.

Data Set

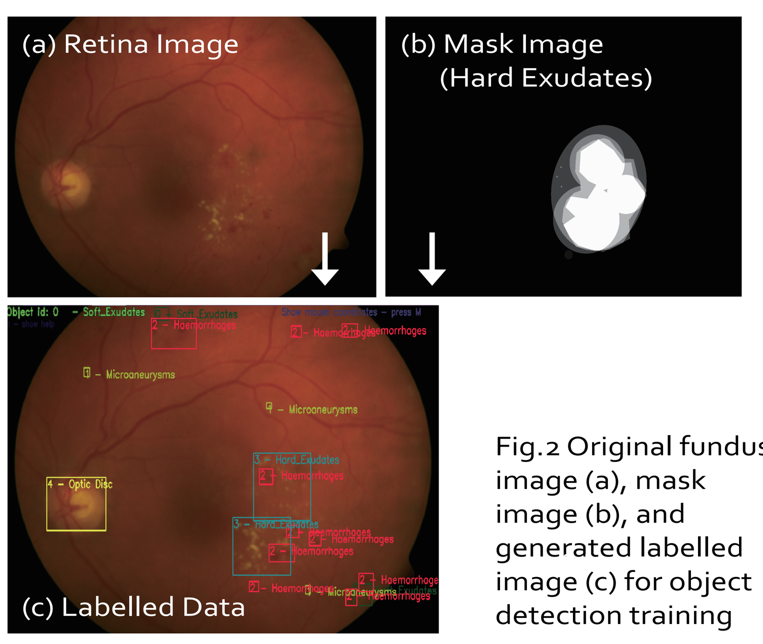

Fig.2 Original fundus image (a), mask image (b), and generated labelled image (c) for object detection training

DIARETDB1 - Standard Diabetic Retinopathy Database [2]
IDRiD - Indian Diabetic Retinopathy Image Dataset [3]

- Both dataset contain colour fundus images and mask images of the following five labels: Soft Exudates / Microaneurysms / Haemorrhages / Hard Exudates / Optic Disc
- We picked 100 images from these two dataset and generated bounding boxes for objects detection training by using the ground truth files(Fig.2).

Method

1. Algorithm comparison – Faster RCNN and YOLO

- Faster RCNN [4]
  - Region Proposal network and detection network are trained separately
  - Region Proposal network trained only on the bounding box region
- YOLO – You Only Look Once [5]
  - Single network for both bounding box and classification
  - Train by whole image, preserve whole image information

	Faster-RCNN	YOLO
Resource requirement	Large	Small
Inference latency	High	Low
Computation complexity	High	Low
Whole image information	No	Yes
Summary	• Able to perform well, even better than YOLO in some performance criteria • Propose extremely more possibility • But demand very high computation power, very high hardware resources	• A balanced trade-off between performance and complexity • Potential of widely usage in resource-constrained device • We choose YOLO to develop more significant approach for Retina image case

Table.1 Quick comparison between Faster-RCNN and YOLO algorithms, we choose to use YOLO in our proposed retina symptoms detection

2. Image Preprocessing - Edge and Color Contrast Enhancement:

- Different feature can have different importance in symptoms detection
- To improve detection performance, we aimed to find the best weighting combination between the original, edge enhanced, and contrast enhanced images with the following formula:

$$\textit{Training Image} = a\,(\text{Original}) + b\,(\text{Contrast Enhanced}) + c\,(\text{Edge Enhanced})\ ,\textit{with } a + b + c = 1$$

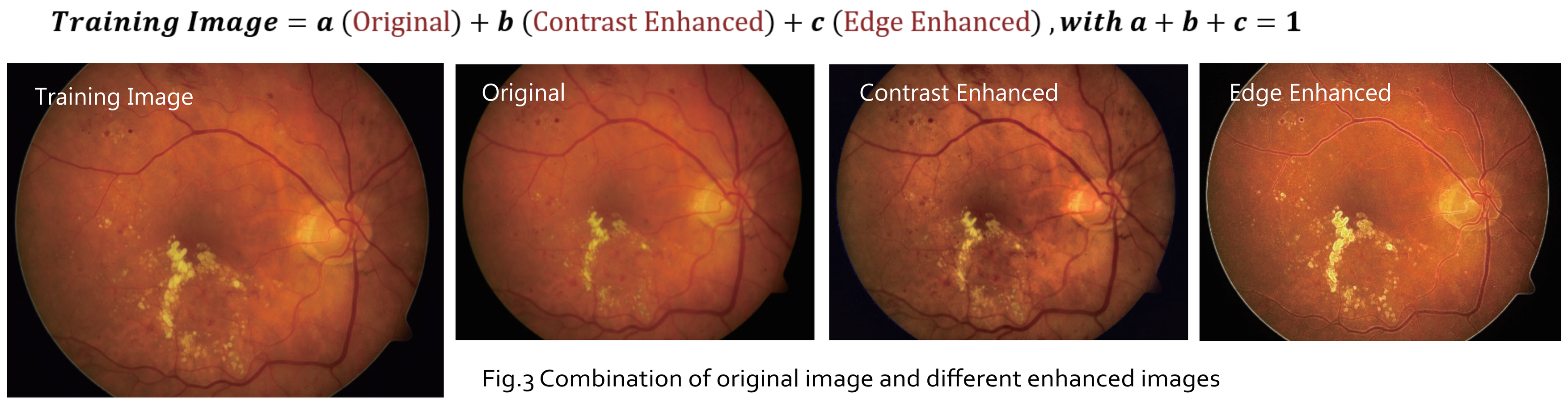

Fig.3 Combination of original image and different enhanced images

3. Performance Metrics:

- Conventional metrics for disease diagnosis:
  - Accuracy: Differentiate the patient and healthy cases correctly

$$Accu = \frac{TruePositive+TrueNegative}{TruePositive+TrueNegative+FalsePositive+FalseNegative}$$

  - Precision: Determined the patient cases correctly

$$Prec = \frac{TruePositive}{TruePositive+FalsePositive}$$

- Modified metrics that is suitable for our object detections task:
  - Area-overlapped based Accuracy and precision:
    - The overlapped area between ground truth and the detected region
  - Case-based Accuracy and precision:
    - Creating a smaller or shifted detected region is still adequate good for symptoms detection
    - Symptoms detected or not -> One-or-zero score

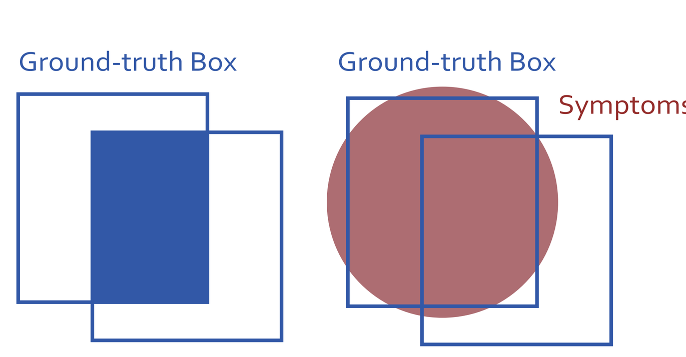

Fig.4 Area-based metrics (left) considers the overlap (blue) region of ground truth and detected box. In case-based metrics (right), the symptoms are considered detected even if the detected box is not perfectly overlap with ground truth box.

Results

1. Performance Tuning by Weighting:

$$\textit{Training Image} = a\,(\text{Original}) + b\,(\text{Contrast Enhanced}) + c\,(\text{Edge Enhanced})\ ,\textit{with } a + b + c = 1$$

(a, b, c)	Area Accuracy	Area Precision	Case Accuracy	Case Precision
(1, 0, 0)	40.3%	71.8%	76%	97.5%
(0, 1, 0)	39.7%	76.7%	78%	100%
(0, 0, 1)	39.3%	**82.1%**	69%	97.5%
(0.5, 0.25, 0.25)	40.0%	78.6%	78%	100%
(0.25, 0.5, 0.25)	40.0%	72.1%	78%	97.5%
(0.25, 0.25, 0.5)	**40.4%**	72.1%	**80%**	**100%**
(0.33, 0.33, 0.33)	40.4%	81.8%	75%	100%

Table.2 Comparison between different weighting combination

- In disease diagnosis, we care much more about accuracy since we can't miss the potential symptoms. (The statement was agreed with cooperating physician.)
- With the setting of more weighting on edge enhancement image, (0.25, 0.25, 0.5), we got the highest case- and area-accuracy

2. Five-fold cross validation

- From the result of performance tuning above, we chose the weighting combination of (0.25, 0.25, 0.5) to perform cross validation.
- We separated the dataset (100 images) to five sets, each contains 80 images for training and 20 images for testing.

	Area Accuracy	Area Precision	Case Accuracy	Case Precision
Set1	37.6%	80.3%	66%	100%
Set2	36.7%	77.2%	75%	100%
Set3	43.7%	81.7%	78%	100%
Set4	40.4%	72.5%	80%	100%
Set5	43.9%	83.9%	70%	97.5%
Average	**40.5%**	**79.1%**	**73.8%**	**99.5%**

Table.3 Cross-Validation result of our model

Discussion

1. Conventional object detection on retina images

- Two most common conventional methods for static object detection:
  - Pattern matching:
    (1) The pattern need to be almost the same
    (2) Human retina different from person to person (Not standardized objects, e.g. car, phone)
  - Background cancelation
    (1) It is useful when we have pre-set white or green background
    (2) Retina images have different color, angle, size, position..., so directly extract background is hard

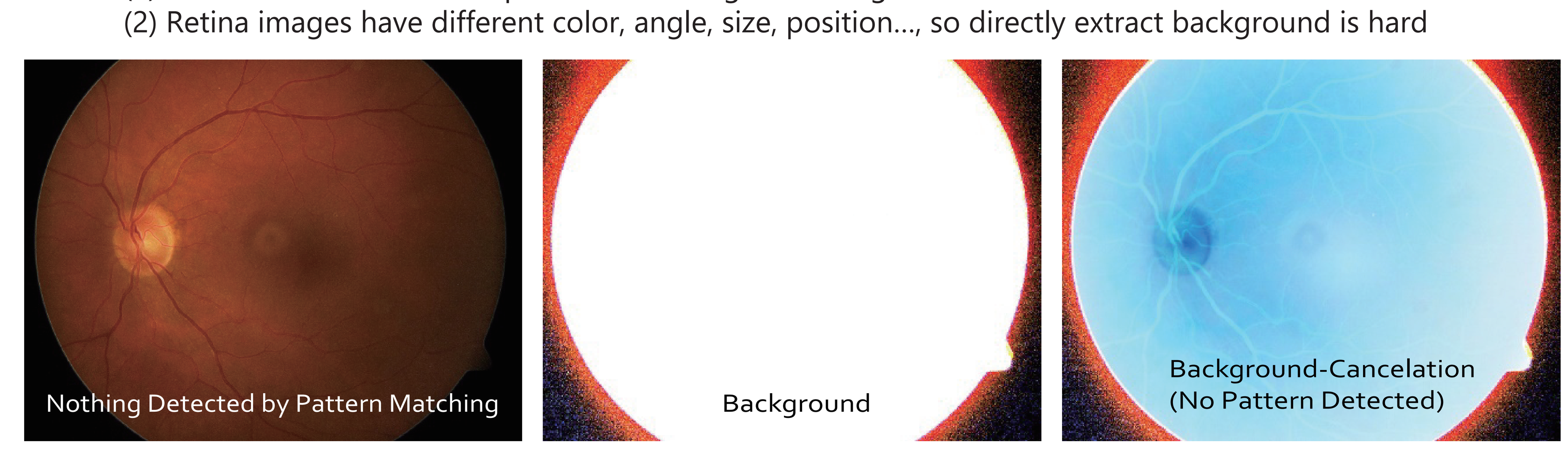

Fig.6 Results of pattern matching and background-cancelation on retain images

2. Proposed DNN-based object detection on retina images

- With our DNN-based object detection model, symptoms on retina images can be detected
- With automatic symptoms detection, doctors can save time finding symptoms on retina images and concentrated more on diagnosis

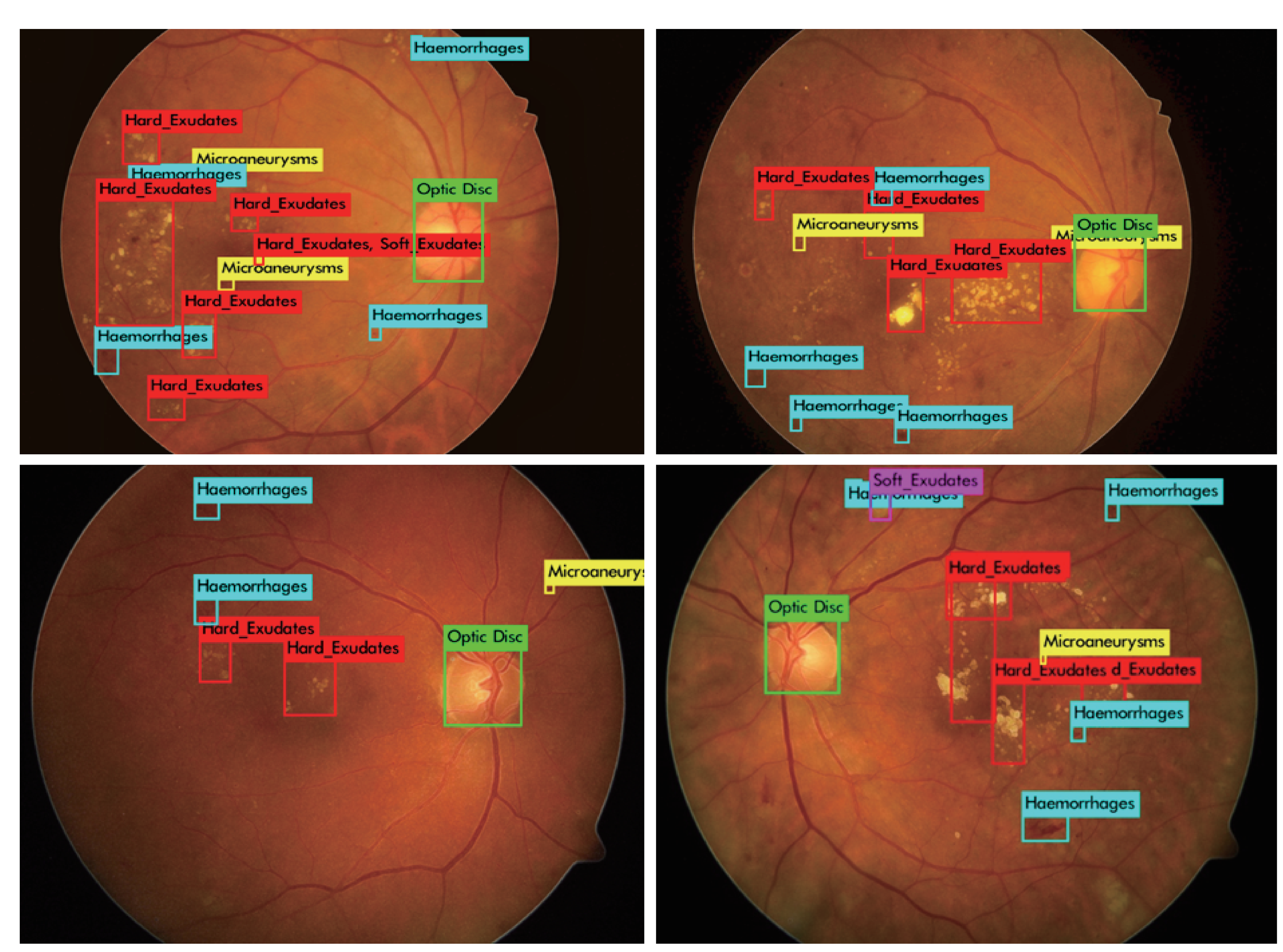

Fig.5 Symptoms detection results on retina images of our trained model

Reference

[1] R. Santhakumar, M. Tandur, E. R. Rajkumar, K. S. Geetha, G. Haritz, and K. T. Rajamani, "Machine learning algorithm for retinal image analysis," In Proc. IEEE Region 10 Conf. (TENCON), Nov. 2016, pp. 1236–1240.
[2] DIARETDB1 dataset: http://www.it.lut.fi/project/imageret/diaretdb1/
[3] IDRiD dataset: https://idrid.grand-challenge.org/Home/
[4] Ren, S., He, K., Girshick, R., & Sun, J. (2015). Faster r-cnn: Towards real-time object detection with region proposal networks. In Advances in neural information processing systems (pp. 91-99).
[5] Redmon, J., Divvala, S., Girshick, R., & Farhadi, A. (2016). You only look once: Unified, real-time object detection. IEEE conference on computer vision and pattern recognition

Acknowledgement

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