Prediction of diabetic retinopathy using machine learning techniques

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ABSTRACT

Diabetic retinopathy (DR) is a complication of diabetes attributed to macular degeneration among patients with type II diabetes. The early symptoms of this disease can be predicted through annual eye checkups. This prediction can help such patients prevent vision loss before the disease progress to retinal detachment. Thus, creating awareness among diabetic patients about this disease is necessary to prevent vision loss. Thus, there is a need to develop a computer-assisted method that can effectively predict the disease. The proposed system uses adaptive histogram equalization (AHE), hop field neural networks, and Adaptive Resonance Theory (ART) for image enhancement, blood vessel segmentation, and blood vessel classification. The proposed system analyzes the disease and classifies the disease level effectively with high accuracy. The system can notify users about the stages of the disease. The proposed system can be evaluated with clinical and open fundus image datasets such as DRIVE, STARE, MESSIDOR, HRF, DRIONS, and REVIEW for DR prediction. Physicians evaluated the system and concluded that the result of the proposed system does not deviate from the quality of disease analysis and grading; the proposed technique achieves 99.99% accuracy. Evaluations conducted by ophthalmologists and witnesses confirmed the quality of the proposed system.

Keywords: Diabetic Retinopathy; Fundus Image; Diabetes; Segmentation; Classification; Feature Extraction.

INTRODUCTION

Diabetes is characterized by an increase in glucose levels and a deregulation of insulin in the human body. When insulin is not sufficiently regulated, it is referred to as type I diabetes; when it is overregulated, it is referred to as type II diabetes. Diabetic retinopathy (DR) occurs among patients with type II diabetes (Varun et al., 2016) and affects the retina, which is a vital organ for vision. When light hits the retina, photoreceptors convert the light into electrical signals, which are then passed from the retina to the brain. DR blocks the blood flow into the retina, causing macular degeneration. Rubbing the eyes can cause the blood vessels to burst and the proteins and lipids to settle inside the retina, causing microaneurysms, cotton wool spots, and exudates, and this can lead to vitreous hemorrhage (Francis et al., 2016). This can also lead to neovascularization, which is the abnormal growth of new blood vessels inside the retina. These abnormal blood vessels can blur the patient's vision, causing them difficult in recognizing objects. Given this retinal vessel impediment, the abnormal blood vessels need to be broken down. At the early stage, photocoagulation and laser treatments are viable options. However, patients can go completely blind without timely treatment.

DR is classified into nonproliferative DR (NPDR) and proliferative DR (PDR) (Jemima et al., 2018). NPDR indicates DR in its initial stages, and PDR indicates the advanced stage of DR. Based on the number of microaneurysms, hard and soft exudates, red and white lesions, the disease can be graded into mild, moderate, or severe levels. Therefore, analyzing the retinal image accurately is a critical task. While analyzing the fundus images of the retina, intensity-wise variations are observed between the tiny blood vessels and the background image. Retinal depigmentation melds the vessels in the image, making it difficult to separate them from the background. An error in identifying the original blood vessel can lead to the formation of a wrong vessel vasculature. Given this context, an image segmentation method is proposed in this paper to segment blood vessels at their cross limits when they overlap other variations from the norm. Further, a detailed survey on various issues in the retinal blood vessel and lesion segmentation was conducted, and the findings of the investigation were used as the reference.

Existing retinal blood vessel and lesion segmentation methodologies are well suited for any sort of fundus image database. Most segmentation algorithms rely on the accuracy of the preprocessed image inputs (Gwenole et al., 2008), and thus far, various researchers have proposed algorithms for extracting blood vessels from retinal images. However, these procedures work effectively only on images from the fundus dataset.

Azzopardi et al. (2015) plotted a BCOSFIRE channel; however, its execution is affected by its boundaries. Franklin et al. (2014) used the multilayer perceptron model and achieved a low precision value because of its pixel processing approach. Ramani et al. (2016) used principal component analysis (PCA) and k-means techniques. The algorithm produced the best precision value; however, it significantly decreased sensitivity. Rajaby et al. (2016) presented an NWFCM calculation for identifying the blood vessels and tracking the vessel direction. This nonlinear technique causes issues in the transmuted space from the low dimensional space when tracking the vessels because of its complex topology.

The existing literature also reports on the several challenges faced while segmenting exudates. Carla et al. (2015) developed an ant colony optimization technique for exudate segmentation. However, this algorithm cannot detect exudates that are not matched by the target threshold value, is rigid, and cannot be generalized for unknown scenarios. Therefore, the algorithm needs further improvements before employing it for clinical practice. All surveyed papers aimed at achieving precise segmentation results. The significance and the adaptive nature of the proposed hop field neural network and adaptive resonance theory (ART) helps achieve better segmentation results compared to that when using the existing methods. ART improves the classification accuracy of DR in an unsupervised manner for early prediction. That is, the proposed method is not confused by the features of hemorrhages and microaneurysms, and it can successfully locate large pathological components as well.

METHODS

Fundus images are used for the diagnosis of DR. Publicly available fundus images are captured by technicians at different fields of view (FoV), which is the optical angle of view of the lens in the fundus cameras. An angle of 30° is 2.5 times the size of a film's picture compared to the typical viewing angle. Wide-angle fundus cameras capture images between 45° and 140°, providing a proportionally lower retinal enlargement. A narrow fundus camera obtains images at an angle of vision of 20° or less. However, these fundus images are captured under different illumination conditions and can contain noise, which need to be eliminated using image enhancement techniques.

Table 1 Fundus image dataset for experiments.

Database	Dimension (pixels)	No. of Images	Infected Images
DRIVE	565x584	40	7
STARE	700x605	400	338
REVIEW	2160x1440	16	7
HRF	3504x2336	15	-
DRIONS	600x400	110	8

For this study, the following publicly available datasets were used: DRIVE, STARE, MESSIDOR, HRF, DRIONS, and REVIEW. The dimensions of these datasets are listed in Table 1. A total of 581 pictures were utilized for the DR experimental analysis.

PROPOSED ARCHITECTURE OF BLOOD VESSEL SEGMENTATION

The hop field neural network algorithm measures the width of the retinal vessels of the fundus images and segments the vessel edges simultaneously. As shown in Figure 1, theproposed architecture has five primary phases:

(1) A mask is generated and applied over the image to remove background pixels.

(2) Image quality is assessed to reject poor-quality images.

(3) Blood vessels are segmented.

(4) The vascular map is identified and tracked

(4) Blood and nonblood vessels are classified

(5) DR is graded.

The proposed strategy utilizes different image processing techniques such as histogram matching, edges detection, Hopfield neural network, and ART.

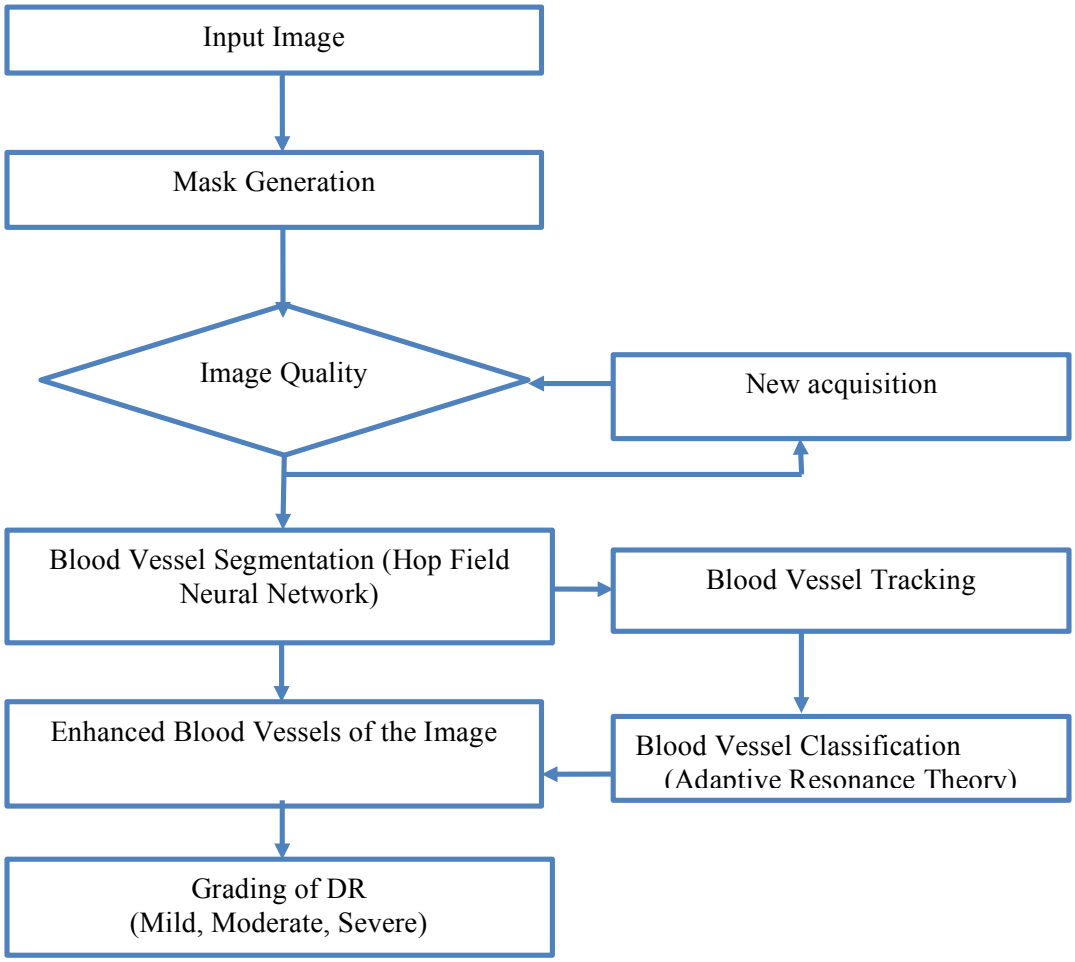


Figure 1 The proposed architecture to diagnose DR.

FUNDUS IMAGE PREPROCESSING

The illumination conditions of the camera can affect the captured images. The fundus camera has to be tilted to different FoVs to capture the right and left eyes of the patients. The proposed system uses an adaptive histogram equalization (AHE) technique for image enhancement. AHE is commonly employed to optimize the gray scale intensity of fundus images. A probability distribution function dynamically expands the gray picture to increase the intensity of the green channel of the blood vessel pixels. The global histogram equalization technique is used to enhance the preprocessing speed. This technique automatically determines the gray picture level and adjusts the optimum histogram value between the neighboring gray level pixels as per the threshold. Thus, the histogram equalization technique uses gray pixels and transforms the histogram to a single image with distinct gray levels and continuous smoothness. The final contrast-enhanced histogram image is obtained using $P(I_E)d_{IE} = P(I_G)D_{IG}$, where I_G represents the gray level value of the input fundus image and $P(I_G)$ represents the probability density Function of the image.

MASK GENERATION

In the mask generation process, pixels within the region of interest (ROI) are marked as vessel pixels. The pixels outside the ROI in the dark or dull region with an intensity value of 0 are disposed before passing the images to the next phase.

HOPFIELD NEURAL NETWORK

Hopfield neural networks are developed from the artificial neural network neurons, which have N inputs. As shown in Figure 2, for every input i, w_i denotes the associated weight. Each input x_i is estimated and the aggregated weight is determined as $w_i x_i$. This weight is represented as a matrix $\boldsymbol{w}$. The components of the weight matrix are denoted as w_{ij}. Therefore, $\boldsymbol{w}$, the refreshing principle of neurons and the neuron's movement in the system are based on characterized rules.

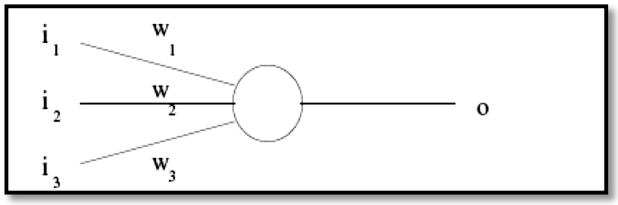


Figure 2 Structure of Hopfield Neural network.

There are two approaches to refresh the network. One approach is to use an asynchronous method, where the network picks one neuron and computes the total input weight and updates it right away. In the second approach, i.e., the synchronous method, the aggregate of input weights of the corresponding neuron is updated without refreshing the network. The pattern is programmed by assigning specific values to all nodes or a specific node. The value of the node is updated once for all iterations using the asynchronous or synchronous mode. The iterations are halted when the nodes reach the highest threshold. The neuron observes corresponding patterns to produce an output. The hop field neural network generates the pattern and represents it by a weight matrix. These patterns are symmetric and have no self-associations. The neurons find the symmetry patterns and update the weight matrix as $w_{ij} = w_{ji}$ neurons to find the no self-association mode, and then all weights are set as $w_{ij} = 0$.

WEIGHT MATRIX GENERATION FOR A PATTERN RECOGNITION

When the weight of the two neurons in the network is positive, then both neurons move in the same direction; this is evident in larger networks. Assumethat the network has neuron i associated with neuron j with a weight +1. At that point, the commitment of neuron i to the weighted input entirety of neuron j is certain if $x_i = 1$ and negative if $x = -1$. At the end of the iteration, neuron i attempt to drive neuron j with a similar incentive. On the off chance that the association loads between them are negative, neuron i will attempt to drive neuron j to the contrary worth. The network can store the uncorrupted design in its memory. Such systems are called Hopfield memories is represented by eqn.(1).

$$Output = \begin{Bmatrix} 1 & : & \sum w_i x_i \geq 0 \\ -1 & : & \sum w_i x_i < 0 \end{Bmatrix} \quad (1)$$

ADAPTIVE RESONANCE THEORY - 1 FRAMEWORK

The ART1 framework includes two significant subsystems, an attentional subsystem, and an orienting subsystem. The framework designs the coordinating activity during which the system structure decides if the input design is among the patterns recently placed in the network. The attentional subsystem has the following features:

- Input neurons of layer F1, which is the correlation layer of transient memory.
- Output neurons of layer F2, with is the acknowledgment layer of short-term memory.
- Gain control unit (Gain 1 and Gain 2; one for each layer).

The subsystem has a long-term memory (LTM) with the following features:

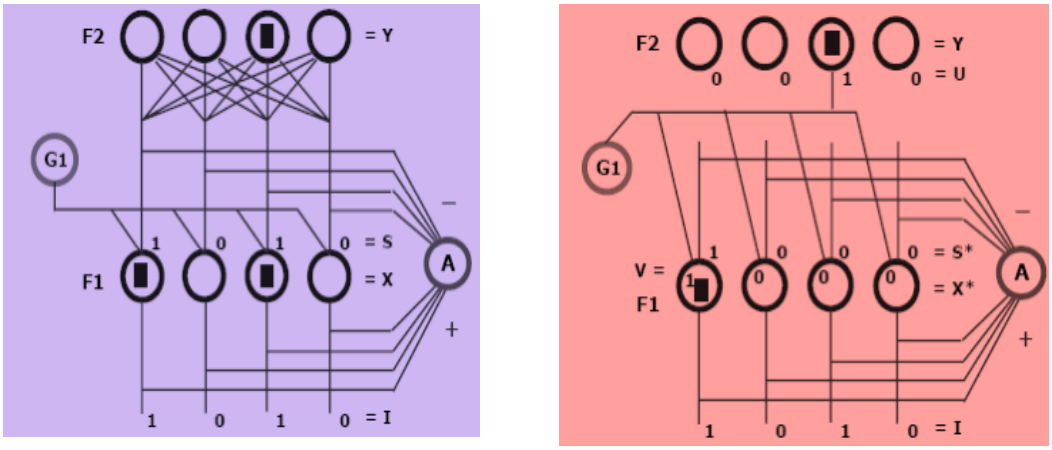
- Interconnections do not appear among the nodes in each layer.
- Inhibitory association of negative weights for gain control from layer F2.
- Constituting the excitation association of positive weights from gain control to layers F1 and F2.

The subsystem has a situating subsystem, which has the following accccompanying layers:

- Reset layer for controlling the attentional subsystem and large elements.
- Inhibitory association of negative weights from layer F1 to the reset node.
- Excitatory association of positive weights from the reset node to layer F2.

ART1 PATTERN MATCHING CYCLE

The ART1 network structure coordinates and attempts to determine if an input design is among patterns recently placed in the system. The pattern matching techniques include the input pattern, pattern matching techniques, reset activities, and finalacknowledgment. As shown in Figure 3, the principle design x is restored on layer F1 and another pattern of coordination is started. Thus, another pattern Y is restored on layer F2. The patterns are generated till a perfect match is obtained for the pattern input, or if layer F2 produces the patterns.



(a) (b)

Figure 3 ART1 system: (a) Input pattern, (b) Pattern matching.

If no match is found, the framework generates the new pattern by disposing the uncertain nodes of layer F2. The learning process during LTM updates the weights. Thesetraining processes continuously process the input and generate the pattern. If any signals pass over the association state, the weights of the associations are modified by the generated pattern. The jumbles do not lead to loss of information or learning the wrong affiliation. The time required to generate the weights depends on the overall coordination of inputs and patterns in the associated network. The association taking an interest in a mismatch cannot sufficiently affect the related weights. When a match is found, the reset signal is not generated to reset the state. Further, the generated associated patterns for the corresponding inputs are dynamic, and they stay in the network for a long time till the weight is finalized by the network. This process continues till layer F2 obtains the required matched pattern. The jumbles do not realize the loss of data or learning of an inappropriate connection related to organized cycle time and the time required to change weights. The association that looks like a mismatch does not affect the related weights. Further, when a match is found, the iterations do not generate the reset signal. The associations never stop until the perfect pattern is generated. This can be achieved by delaying the dynamic pattern generation process by strengthening the weights.

RESULTS AND ANALYSIS

A key inspiration for the proposed strategy is improving the nature of fundus images through image enhancement and segmentation. Despite considerable research in this domain, there is still a need for the precise prediction of malignancy for clinical diagnosis. Given this context, programmed retinal vein segmentation and lesions strategies were introduced in the proposed work. The proposed technique considered 581 images obtained from different public fundus datasets. Figure 4 shows the segmentation of the lesions. The infected retinal images are graded after segmentation as follows:

Case 1: If there is only one microaneurysm in the image, the grade is very mild.

Case 2: If there are microaneurysms, retinal hemorrhages, exudates, and cotton wool spots, the grade is mild.

Case 3: A moderate case where venous beading is observed in multiple quadrants,hemorrhages are observed in one to three quadrants, and cotton wool spots are present.

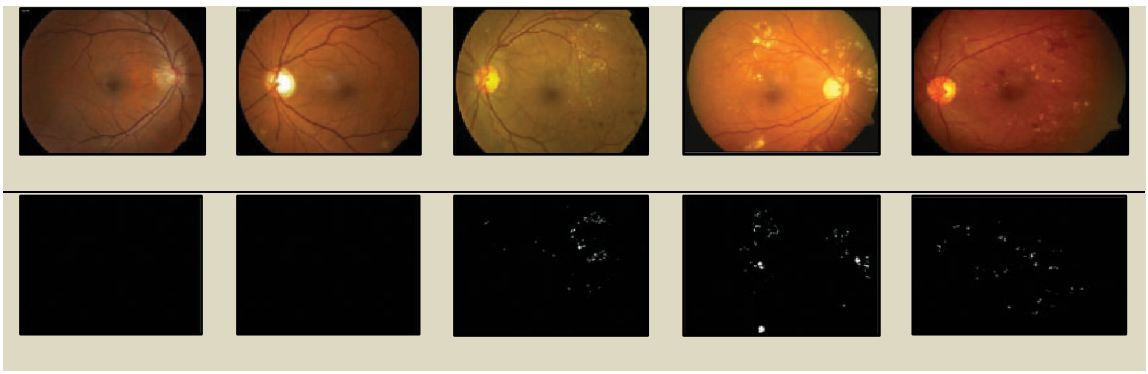
Case 4: If there are large amounts of hemorrhages in all quadrants and venous beading is observed in at least two quadrants, then it is graded as severe.

Case 5: At a very severe stage, lesions will exist in more than two quadrants.

(a) (b) (c)

Figure 4 (a) Image with depigmentation (b) & (c) Segmentation of lesions.

As shown in Figure 5, microaneurysms, hemorrhages, exudates, and lesions in the mild stage are present in any or all parts of the image. In the moderate stage, the first three quadrants show retinal hemorrhages, and more than one quadrant shows venous beading along with cotton wool spots. The severe stage contains severe retinal hemorrhages in all quadrants and significant venous beading in more than two quadrants.



(a) (b) (c) (d) (e)

Figure 5 Grading of diabetic retinopathy: (a) Standard Retina (b) Mild case, (c) Moderate case, (d) Severe case, (e) Very severe case.

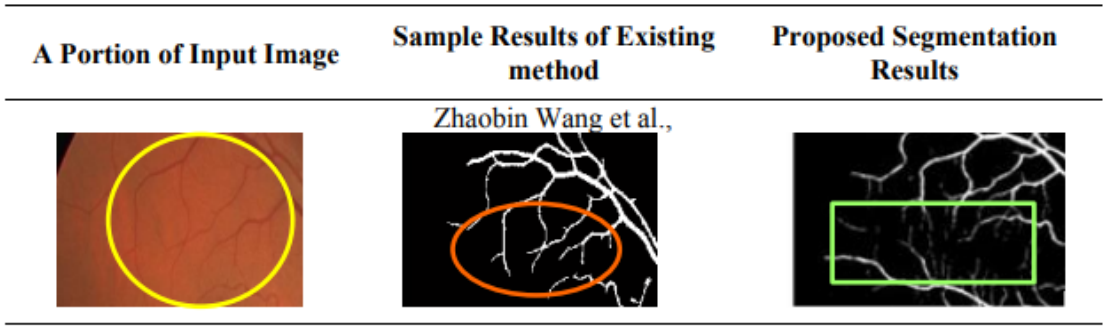


Figure 6 Comparison of tiny vessel detection with competitive methods.

In Figure 6, column 1 shows the source image with small vessels that are hard to detect,column 2 shows the methodology that failed in identifying the small vessels when using competitive methods, and column 3 shows the small vessels that hard to detect being discovered by the proposed method.

PERFORMANCE METRICS

Generic parameters such as sensitivity, specificity, and accuracy are considered to measure the performance of the segmentation and classification techniques for DR. SE & SP measurements are performed around the grouped vessel and non-vessel pixels, individually. Acc represents the general measure for the proportion of all absolute vessel pixels. These measurements are utilized to observe the nature of the outcomes from the blood vessels, lesions segmentation, and classification.

$$Se = \frac{TP}{TP + FN}$$

(2) $$Sp = \frac{TN}{TN + FP}$$

(3) $$Acc = \frac{(TP + TN)}{(TP + FN + TN + FP)}$$

(4)

Table 2 Proposed segmentation results vs. existing segmentation techniques.

#	Segmentation Techniques	Sn	Sp	Acc
1.	Shuangling Wang et al. [21]	0.8173	0.9733	0.9475
2.	Lei Zhanga et al. [31]	0.7812	09668	0.9504
3.	Sohini Roychowdhury et al. [2]	0.7280	0.9830	0.9520
4.	R. GeethaRamani et al. [16]	0.7079	0.9778	0.9536
5.	YuQianZhao et al. [42]	73.54	97.89	94.77
6.	Lei et al. [43]	78.10	96.70	95.10
7.	Argyrios Christodoulidis et al. [38]	0.8506	0.9582	0.9479
8.	Sudeshna Sil Kar et al. [39]	0.7632	0.9801	0.9628
9.	Shahab Aslani et al. [40]	0.7545	0.9801	0.9648
10.	Nagendra Pratap Singh et al. [12]	0.7594	0.9801	0.9522
11	Shailesh Kumar et al. [37]	0.8700	0.9300	-
12.	**Proposed Technique**	**0.9998**	**0.9997**	**0.9999**

Table 2 shows that the proposed algorithm outperforms other deep learning techniques. Recurrent neurons are trained to adjust the image features to predict a small object that necessitates more contexts. The proposed approach accomplished a normal estimation with 99.98% sensitivity, 99.97% specificity, and 99.99% accuracy compared to those of competitive methods.

CONCLUSION

Detecting anomalies presented in the retina helps physicians employ dynamic procedures to diagnose DR. The proposed indicator diminishesthe false negatives and provides dependable recognition precision in terms of position and mass size. Further, the proposed system accurately detects both minor and major blood vessels and lesions from the infected fundus images. In addition, the method detects blood vessels that are difficult to diagnose, for example, where many small and vague drusen are present in the retina. The proposed HopField neural network algorithm is an unsupervised method that significantly reduces the probability of error occurred when compared to that using other supervised methods. This algorithm segments the depigmented image and increases the exhibition of the system. ART is included in the system to classify the retinal blood vessel image and lesions to grade the level of DR images obtained from the public databases and clinical images.

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