RVPD: AN AUTOMATED SYSTEM FOR CALCULATING THE TORTUOSITY AND BIFURCATION ANGLES OF RETINAL VESSELS TO PREDICT DISEASES

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ABSTRACT

Hypertension and diabetes are known to potentially cause morphological changes in the retinal capillary system, yet quantifying these changes presents significant challenges. This research addresses this issue by designing and developing an automated system capable of analyzing retinal images to detect and measure these changes. Our system automatically segments vessels and the optic disc, calculates tortuosity and bifurcation angles, and performs disease prediction based on these measurements along with clinical features. For tortuosity calculation, we adopted a novel curve fitting method, which provides more stable convergence compared to traditional discrete numerical methods. The system integrates clinical data and conducts prediction experiments on hypertensive and diabetic patients with varying sample sizes. Our results demonstrate the system's strong performance and scalability: in the hypertension group, the AUC reached a maximum of 0.814 ± 0.023, with an ACC of 0.735 ± 0.033, while in the diabetes group, the AUC reached a maximum of 0.710 ± 0.043, with an ACC of 0.641 ± 0.052. These findings suggest that our automated system could serve as a valuable tool for early detection and risk assessment of hypertension and diabetes, potentially improving patient outcomes through timely intervention.

***Index Terms*—** Retinal vessel segmentation, Tortuosity, Bifurcation, Hypertension, Diabetes

1. INTRODUCTION

Hypertension and diabetes represent significant global health burdens, necessitating advanced methodologies for early diagnosis and prognosis. Recent studies [1][2] have elucidated a correlation between these systemic vascular pathologies and morphological alterations in the retinal microvasculature, specifically manifesting as changes in vessel tortuosity and bifurcation angles. This association provides a unique opportunity for non-invasive diagnostic techniques through quantitative analysis of retinal vascular geometry.

The advent of deep learning architectures [3], particularly the U-Net convolutional network [4], has revolutionized medical image segmentation, achieving unprecedented accuracy in delineating ocular vascular structures. This high-precision segmentation serves as a crucial precursor for precise quantification of vascular morphometrics, including tortuosity indices and bifurcation angles. However, despite these advancements, there remains a notable absence of a comprehensive, automated system that integrates these multiple vascular parameters for disease classification.

To address this critical gap in clinical informatics, our research presents a novel, fully automated system that synergistically combines retinal vessel segmentation, quantitative analysis of arterial and venous tortuosity, bifurcation angle measurement, and machine learning-based disease prediction. A key innovation in our methodology is the implementation of a curve fitting algorithm for tortuosity calculation. This approach represents a significant departure from conventional methods, such as proprietary software solutions [5] or discrete point interpolation techniques [6]. Our method employs a more mathematically rigorous approach, transforming vascular images into single-pixel-wide skeletons and applying continuous curve fitting for tortuosity quantification.

The utilization of curve fitting for tortuosity analysis offers superior numerical stability compared to traditional discrete methods. By deriving analytic expressions for vessel curvature, we achieve more consistent and accurate results in differentiation and integration processes, crucial for reliable tortuosity measurement. This enhanced precision is fundamental to the overall efficacy of our disease prediction model.

Our integrated system represents a significant advance-

ment in automated medical image analysis, addressing several key challenges in the field. By combining advanced image processing techniques with machine learning algorithms and clinical data integration, we have demonstrated promising results in the prediction of hypertension and diabetes based on retinal vascular morphology. The robust performance and scalability exhibited in our experimental evaluations suggest that this approach has considerable potential for clinical application.

2. METHODS

2.1. Overall Framework

As illustrated in Figure 1, our overall framework begins with several preprocessing steps applied to fundus images. These steps include dark channel prior defogging [7], image cropping and padding, grayscaling, geometric transformations, and histogram equalization. Following preprocessing, two parallel U-net models are employed to segment the optic disc and blood vessels separately. After segmentation, the system optimizes the vessels (e.g., removing capillaries) and classifies them into arteries and veins. The segmentation range of the vessels is then limited to between 0.5 and 2 optic disc calibers away from the disc margin. Subsequently, the system skeletonizes the vessels, detects bifurcation points, performs vector searching, and applies curve fitting, generating the necessary data for further analysis. In the final stage, the system calculates bifurcation angles and tortuosity, combines these measurements with clinical features, and utilizes a multilayer perceptron (MLP) model for disease prediction.

2.2. Bifurcation Angle

To enhance the accuracy of bifurcation angle calculations, we limit the analysis range to between 0.5 and 1 optic disc calibers away from the disc margin. This range limitation reduces unnecessary extensions, thereby improving computational precision. In the post-segmentation black and white images, each vessel is represented as a separate connected component. We transform each vessel into a graph structure for analysis.

In our analysis, we identify nodes with a degree greater than 2 as bifurcation points and eliminate vessels lacking such points. Considering that ocular vessels typically radiate around the center of the optic disc, we select the two points farthest from the disc center and with a node degree of 1 as the bifurcation endpoints.

Let the coordinates of bifurcation point P_0 be $(x_0,\, y_0)$, and the coordinates of the two endpoints be P_1 $(x_1,\, y_1)$ and P_2 $(x_2,\, y_2)$, respectively. The bifurcation angle θ can be calculated using the following formula:

$$\vec{v_1} = (x_1 - x_0, y_1 - y_0) \tag{1}$$

$$\vec{v_2} = (x_2 - x_0, y_2 - y_0) \tag{2}$$

$$\theta = \arccos \frac{\vec{v_1} \cdot \vec{v_2}}{||\vec{v_1}|| \cdot ||\vec{v_2}||} \tag{3}$$

2.3. Tortuosity

According to Hart [8], we define the vascular curve C, where the x and y coordinates satisfy the parametric equations $\begin{cases} x=x(t) \\ y=y(t) \end{cases}$, with t ranging from $[t_0,\, t_1]$. At point t, the curvature $\kappa(t)$ of curve C is defined as:

$$\kappa(t) = \frac{x'(t)y''(t) - x''(t)y'(t)}{[x'(t)^2 + y'(t)^2]^{\frac{3}{2}}} \tag{4}$$

Next, calculate the total squared curvature of curve C:

$$tsc(C) = \int_{t_0}^{t_1} [\kappa(t)]^2 dt \tag{5}$$

The arc length $(s(C))$ of curve C is defined as:

$$s(C) = \int_{t_0}^{t_1} \sqrt{x'(t)^2 + y'(t)^2} dt \tag{6}$$

Therefore, the tortuosity of curve C is calculated as:

$$Tortuosity = \frac{tsc(C)}{s(C)} \tag{7}$$

In numerical calculations, it is common to use discrete points to approximate the derivatives and integrals of the curve to estimate tortuosity. In computer images, the spacing between adjacent pixels of the vascular curve is typically 1 or $\sqrt{2}$, which affects the calculation of total squared curvature since it involves taking derivatives followed by integration. Although the discrete method is feasible when precision requirements are low, the small values of arterial and venous tortuosity make them highly sensitive to minor disturbances, leading to varying results from different discrete calculation methods.

This study adopts curve fitting methods to calculate tortuosity. First, to ensure a one-to-one functional relationship of the (x, y) coordinates for each curve, we rotate the vascular curves to a horizontal position and remove bifurcation points. Then, we fit using an appropriate curve model. Finally, we ensure the convergence of the tortuosity values through numerical derivatives and integration methods such as SciPy [9].

3. EXPERIMENTS

3.1. Datasets

Segmentation data: For the separate training of U-net models for vessel and optic disc segmentation, this study employed two different datasets. The vessel segmentation model

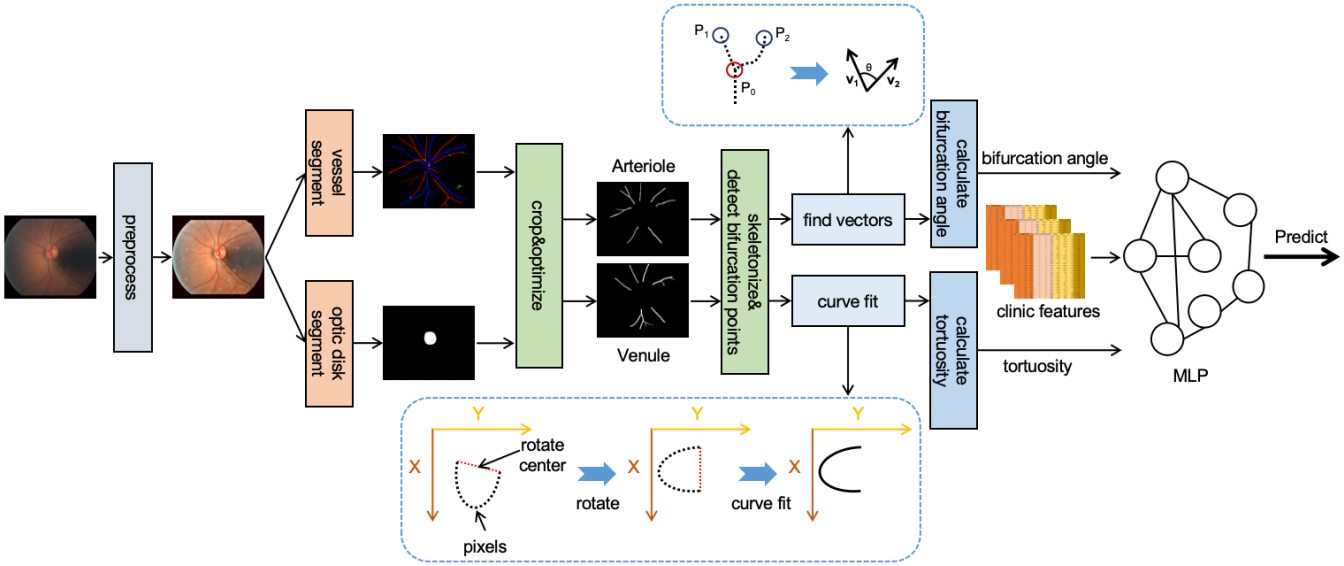


Fig. 1: Illustration of RVPD, An automated system for calculating the tortuosity and bifurcation angles of retinal vessels, and for predicting associated diseases. The RVPD system enhances image quality through various preprocessing techniques and employs a dual parallel data stream approach to boost processing efficiency. This system shares certain steps in the calculation of tortuosity and bifurcation angles, thereby optimizing the overall computational workflow. Ultimately, by integrating clinical features, the RVPD successfully achieves effective disease prediction.

utilized 149 fundus images, annotated by professional doctors with arteries, veins, and their intersections, with 120 images for training and 29 for evaluation. The optic disc segmentation model used the publicly accessible Indian Diabetic Retinopathy Image Dataset (IDRiD) [10] and was trained in conjunction with unlabeled data from our Research.

Prediction data: The prediction dataset includes clinical data and left eye images of 2080 patients, covering gender, age, body mass index, current smoking, current drinking, lipid, kidney function, and various related indicators [11][12]. Hypertension was defined as any self-reported history of hypertension, systolic blood pressure (SBP) $\geq$ 140 mmHg, diastolic blood pressure (DBP) $\geq$ 90 mmHg, or use of blood-pressure-lowering treatment. Diabetes was defined as any self-reported history of diabetes, index abnormality [fasting blood glucose (FBG) $\geq$ 7.0 mmol/L, or use of glucose-lowering treatment. To balance the data, samples from both diseased and non-diseased patients were equalized through random sampling. Among them, there are 896 patients with hypertension and 375 with diabetes.

3.2. Implementation

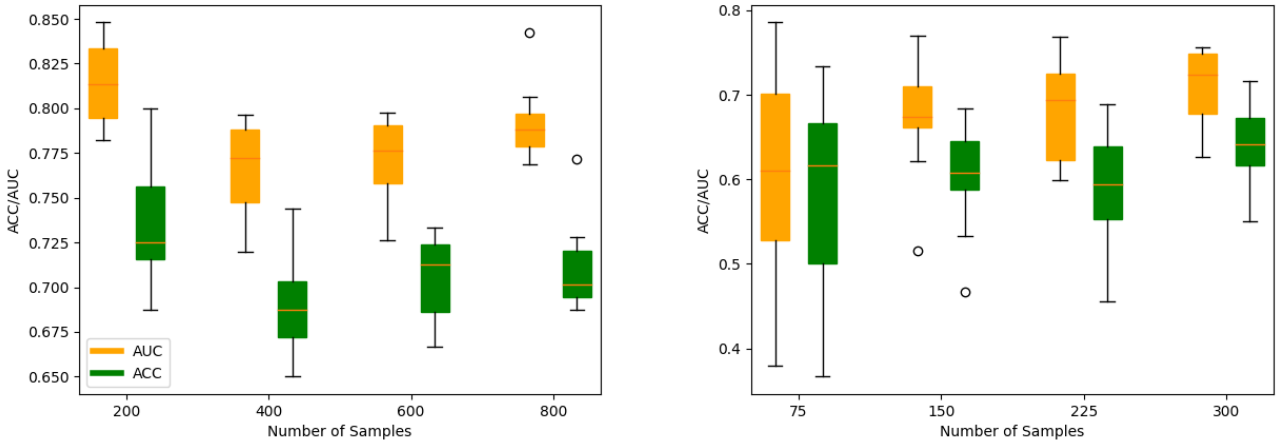
In implementation, the U-net model serves as the backbone, with the Epoch set to 2000 and the initial learning rate at 0.0003. The vessel segmentation model uses the Adam optimizer [13] with a cross-entropy loss function. The optic disc segmentation model, due to smaller data volumes, employs Mixmatch [14] augmentation, uses an SGD optimizer, and sets the loss function as Lx (BCE loss) weighted with Lu (MSE loss), where the weight u of Lu increases gradually during training. The optimal model is selected based on its performance on the validation set. All codes are implemented with PyTorch [15].

Tortuosity calculation is achieved by fitting spline curves to vascular curves, involving computation of derivatives and integrals. This study uses functions from scientific computing libraries to perform these calculations, optimizing the fitting quality by adjusting the smoothing parameters of the spline curves, thus promoting effective convergence of the integrals.

To predict hypertension and diabetes, this study uses a multilayer perceptron (MLP) model with a single hidden layer (comprising 8 hidden units). The model uses an Adam optimizer with an initial learning rate of 0.001, a weight decay of 0.005, and a learning rate scheduler set to ExponentialLR with a gamma value of 0.96. The training runs for 100 epochs, with a batch size of 64, using five-fold cross-validation. To prevent information leakage, blood pressure indices are excluded from hypertension prediction, and blood glucose indices are excluded from diabetes prediction. Area Under Curve (AUC) and Accuracy(ACC) are used to evaluate the predictive performance of the model.

3.3. Experiments Set

To ensure the adequacy of the experiments, four groups were established for each disease, with each group randomly selecting an equal number of diseased and non-diseased indi-



(a) hypertension

(b) diabetes

Fig. 2: Results of the predictions

viduals from the total sample. The hypertension groups are as follows: HY-1, HY-2, HY-3, and HY-4, containing 200, 400, 600, and 800 hypertension patients respectively, along with an equal number of healthy individuals. The diabetes groups are DM-1, DM-2, DM-3, and DM-4, with 75, 150, 225, and 300 diabetes patients respectively.

4. RESULTS AND DISCUSSION

As illustrated in Figure 2 and Table 1, the hypertension group demonstrated robust performance, achieving a maximum AUC (%) of 81.4 ± 2.3 and an ACC (%) of 73.5 ± 3.3. These results indicate the system's strong predictive capability for hypertension.

The diabetes group, initially constrained by sample size, showed slightly lower metrics when the number of positive samples was 75. However, the predictive performance improved markedly as the sample size increased. With 300 samples, the AUC (%) reached a maximum of 71.0 ± 4.3, and the ACC (%) was 64.1 ± 5.2. This trend suggests that further increases in sample size could lead to continued improvements in predictive performance.

The observed fluctuations in prediction metrics can be attributed to the diverse physical symptoms and clinical characteristics exhibited by hypertension and diabetes patients. This variability is partly related to the sampling method employed in the study.

Notably, even after excluding key diagnostic indicators for hypertension and diabetes (such as systolic pressure, diastolic pressure, and blood glucose), the system still produced impressive prediction results. This finding underscores the system's broad applicability and significant clinical potential, as it demonstrates the ability to predict these conditions using alternative, less obvious indicators.

	HY-1	HY-2	HY-3	HY-4
AUC(%)	81.4±2.3	76.6±2.4	77.2±2.2	79.2±2.0
ACC(%)	73.5±3.3	69.2±2.9	70.5±2.2	71.1±2.4
	DM-1	DM-2	DM-3	DM-4
AUC(%)	60.3±12.0	67.1±6.5	68.2±5.9	71.0±4.3
ACC(%)	58.3±11.4	60.2±6.0	59.1±6.7	64.1±5.2

Table 1: AUC and ACC for hypertension and diabetes groups

5. CONCLUSION

In conclusion, we have developed an automated system that accurately calculates the tortuosity and bifurcation angles of arteriovenous vessels in fundus images, effectively predicting hypertension and diabetes by leveraging these vascular characteristics alongside other clinical indicators. Our system demonstrates robust scalability, maintaining high predictive accuracy across datasets of varying volumes. This research not only advances computer-aided diagnosis but also provides a practical tool for early detection and risk stratification of systemic vascular diseases. The capacity to non-invasively assess vascular health through retinal imaging could significantly impact patient care, enabling more timely interventions and personalized treatment strategies. As we continue to refine and validate this technology, it holds promise for broader applications in vascular health assessment and disease management, potentially revolutionizing early detection and treatment of systemic vascular conditions.

6. COMPLIANCE WITH ETHICAL STANDARDS

This study was performed in line with the principles of the Declaration of Helsinki. This study was approved by the ethics committee of Peking University First Hospital (2014[700]).

7. ACKNOWLEDGEMENTS

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