Predicting Choroidal Vascular Abnormalities in High Myopia with Longitudinal OCTA Analysis and Data-Driven Modeling

Abstract: High myopia is prone to induce choroidal vascular lesions, which severely affect visual acuity. The aim of this research is to achieve effective prediction of choroidal vascular lesions in high myopia through longitudinal optical coherence tomography angiography (OCTA) analysis and data-driven modeling. During the research process, a large amount of longitudinal OCTA image data of high-myopia patients was collected. Firstly, image pre-processing algorithms were utilized to perform operations such as denoising and enhancement on the original images to improve the image quality. Subsequently, the Convolutional Neural Network (CNN) in deep-learning algorithms was adopted to extract and analyze image attributes, and to excavate key attributes such as the morphology and structure of choroidal blood vessels. On this basis, combined with time-series analysis methods, a data-driven model was constructed. The experimental results demonstrate that this model can accurately predict the occurrence and development of choroidal vascular lesions in high myopia, providing strong support for early clinical intervention.

Keywords: High Myopia; Choroidal Vascular Lesions; Longitudinal OCTA; Data-Driven Modeling; Convolutional Neural Network.

I. INTRODUCTION

With the continuous rise in the incidence of myopia globally, high myopia has emerged as a public health issue that cannot be overlooked[1,2]. High myopia is not merely an increase in refractive power; more importantly, it can trigger a series of severe ocular complications, among which choroidal vascular lesions are particularly prominent. Choroidal vascular lesions can not only lead to a decline in visual acuity but may even cause blindness in severe cases, exerting a substantial negative impact on the quality of life of patients.

Currently, clinical diagnosis of choroidal vascular lesions in high myopia mainly relies on traditional ocular examination methods[3-5]. However, these methods often can only detect the lesions after they have developed to a certain extent, with relatively low sensitivity to early-stage lesions, making it difficult to achieve early warning and intervention of the disease. The advent of OCTA technology has provided a new perspective for the study of ocular vascular lesions. OCTA can non-invasively and with high resolution present the morphology and structure of ocular blood vessels, serving as a powerful tool for studying choroidal vascular lesions in high myopia[6].

Previous research has mostly focused on the analysis of cross-sectional OCTA images. Although this approach can obtain vascular information at a certain time point, it cannot comprehensively reflect the dynamic change process of choroidal vascular lesions over time. Longitudinal OCTA analysis, on the other hand, can compensate for this deficiency[7]. By continuously observing and analyzing the OCTA images of the same patient at different time points, it is possible to more accurately capture the development trend of choroidal vascular lesions.

Simultaneously, data-driven modeling is increasingly being applied in the medical field. It can unearth latent laws and patterns from a vast amount of data, providing a quantitative basis for disease prediction and diagnosis[8,9]. In the study of choroidal vascular lesions in high myopia, combining longitudinal OCTA analysis with data-driven modeling holds the promise of constructing a more accurate prediction model.

This study is carried out based on longitudinal OCTA analysis and data-driven modeling, aiming to utilize advanced image-processing algorithms and deep-learning techniques to deeply explore the characteristic information of choroidal blood vessels in high-myopia patients. Through constructing an effective data-driven model, accurate prediction of choroidal vascular lesions in high myopia can be achieved[10-12]. This not only contributes to deepening our understanding of the pathogenesis of choroidal vascular lesions in high myopia but also provides scientific evidence for early diagnosis and intervention for clinicians, thereby reducing the incidence of high-myopia-related complications and improving the visual prognosis of patients.

II. RESEARCH STATUS

A. *Research Status of Prediction of Choroidal Vascular Lesions in High Myopia*

High myopia, being a prevalent ophthalmic malady, the choroidal vascular lesions it engenders gravely imperil the visual well-being of patients. At present, investigations into the prediction of choroidal vascular lesions in high myopia have attained a certain degree of headway, yet numerous conundrums still persist.

In the realm of clinical practice, conventional prognostic methods chiefly hinge upon the patient's medical annals and ophthalmic examination indices such as intraocular tension and axial ocular length. The axial ocular length is inextricably linked to the progression of high myopia. An unduly protracted axial ocular length can exert mechanical traction on the choroidal tissue, thereby augmenting the risk of choroidal vascular lesions. Nevertheless, the prognostic veracity of these solitary indices is circumscribed, and it proves arduous to comprehensively mirror the latent risks of the lesions.

With the evolution of imaging techniques, optical coherence tomography (OCT) and its derivative technologies assume a pivotal role in the prediction of choroidal vascular lesions in high myopia. Among them, frequency-domain OCT can lucidly exhibit the laminar structure of the choroid, proffering an intuitive foundation for appraising choroidal thickness and morphological alterations. Researches have unearthed that alterations in choroidal thickness are interrelated with the genesis and development of choroidal vascular lesions in high myopia. For instance, in the incipient stage of the lesion, the choroidal thickness might evince a tendency towards attenuation. Nonetheless, relying solely on the analysis of static OCT images renders it formidable to precisely prognosticate the dynamic evolution of the lesion.

Moreover, genetic assay techniques have gradually been applied to the predictive research of choroidal vascular lesions in high myopia. Certain studies have indicated that mutations or polymorphisms of specific genes are associated with the susceptibility to high myopia and its complications. By detecting these genetic markers, it is anticipated to prognosticate the lesion risk at the molecular echelon. However, genetic assay is currently exorbitant in cost, and the clinical elucidation of test outcomes remains incomplete, circumscribing its large-scale application.

B. *Research Status of Longitudinal OCTA Analysis and Data-Driven Modeling*

Longitudinal OCTA analysis proffers a novel avenue for delving into the dynamic vicissitudes of ocular vascular lesions. Traditional OCTA technology preponderantly entails cross-sectional imaging, which is merely capable of procuring vascular information at a given instant. Longitudinal OCTA analysis, through the successive collection and comparative analysis of the OCTA images of the same patient at disparate time points, can track in real-time the morphological, structural, and hemodynamic changes of choroidal blood vessels.

In the domain of ophthalmology, longitudinal OCTA analysis has been enlisted in the research of diverse ocular afflictions, such as age-related macular degeneration and diabetic retinopathy. In the study of choroidal vascular lesions in high myopia, longitudinal OCTA analysis can discern the alterations in the configuration of blood vessel bifurcations, the fluctuations in vascular density, and the emergence and developmental course of neovascularization, furnishing pivotal information for an in-depth comprehension of the lesion mechanism.

Data-driven modeling has emerged as a burgeoning topic in the sphere of medical research in recent years. In the prediction of choroidal vascular lesions in high myopia, data-driven modeling fabricates mathematical models to prognosticate the occurrence and development of lesions by amalgamating a profusion of clinical data, imaging data, genetic data, and the like. Machine learning algorithms such as support vector machines and random forests are extensively employed in attribute selection and model construction. These algorithms can automatically cull key attributes from intricate data and enhance the accuracy of the prediction model.

Deep-learning algorithms, particularly convolutional neural networks (CNNs), have manifested potent advantages in image data processing. In data-driven modeling predicated on longitudinal OCTA images, CNNs can autonomously assimilate the intricate attributes of choroidal blood vessels and effectuate accurate identification and prediction of lesions. Simultaneously, in conjunction with time-series analysis methodologies, the time-dimensional information of longitudinal data can be fully harnessed to further augment the prediction performance of the model. Nevertheless, data-driven modeling also confronts issues such as data quality and model interpretability. How to enhance the reliability and clinical applicability of the model remains the focal point and crux of current research.

III. THEORETICAL BASIS

A. *Optical Coherence Tomography Angiography (OCTA)*

OCTA is a kind of angiographic approach that emanates from the optical coherence tomography technique. Its fundamental tenet is to scan biological tissues with low-coherent light. By gauging the optical path discrepancies of the reflected light from tissues at diverse depths, the three-dimensional structural information of the tissues can be procured. In the realm of angiography, it predominantly relies on the principle of Doppler frequency shift to differentiate between stationary tissues and flowing blood.

Let f_0 be the frequency of the light emitted by the light source. When the light impinges on moving blood cells, in compliance with the Doppler effect, the frequency f of the reflected light experiences a transformation, and the frequency shift Δf is expressed as:

$$\Delta f = \frac{2v\cos\theta}{\lambda} f_0 \#(1)$$

Here, v represents the velocity of the blood cells' movement, θ is the angular deviation between the light ray and the blood-flow direction, and λ is the wavelength of the light. Through the detection of this frequency shift, OCTA has the capacity to discern the blood-flow signals within blood vessels, thereby generating angiographic images. For the choroidal blood vessels of high-myopia patients, OCTA is capable of providing high-resolution data about the blood-vessel morphology, vessel caliber, and vascular density. These data form an essential underpinning for the subsequent analysis of lesion prediction.

B. *CNN*

In the convolutional layer, assume that the input image is $I(x,y)$ and the convolutional kernel is $K(m,n)$. The output attribute map $O(i,j)$ post-convolution operation is given by:

$$O(i,j) = \sum_m \sum_n I\,(i+m, j+n)K(m,n)\#(2)$$

In this formula (i, j) denotes the pixel coordinates within the output attribute map, and(m, n)represents the presents that pixel positions within the convolutional kernel. Through the utilization of multiple convolutional kernels with distinct parameters, diverse types of attributes within the image, such as edges and textures, can be extracted For the choroidal blood-vessel images of high-myopia patients, the convolution operation is effective in extracting the morphological attributes of the blood vessels.

The pooling layer serves mainly to reduce the resolution of the attribute map, cut down on computational complexity, and simultaneously preserve the crucial attributes. Common pooling operations include max-pooling and average-pooling. Taking max-pooling as an example, if the input attribute map is $F(x,y)$ an size of the pooling window is $k \times k$, then the output attribute map $P(i,j)$ is calculated as:

$$P(i,j) = \max_{m=0}^{k-1}\max_{n=0}^{k-1} F(i \times k + m, j \times k + n)\#(3)$$

The pooling operation conducts down sampling on the attributes on the premise of not losing the pivotal information, enabling the model to capture the global attributes of the image more effectively.

The fully-connected layer flattens the attribute map that has been processed through the convolutional and pooling layers and then connects it to the output layer via the weight matrix W and the bias b to realize the classification or prediction of the image. Let the input vector be X and the output vector be Y , then:

$$Y = \sigma(WX + b)\#(4)$$

Here, σ represents the activation function. For instance, the Softmax function is utilized for multi-classification problems. In the prediction of choroidal vascular lesions in high myopia, the fully-connected layer can predict the probability of lesion occurrence based on the extracted attributes, see Fig.1.

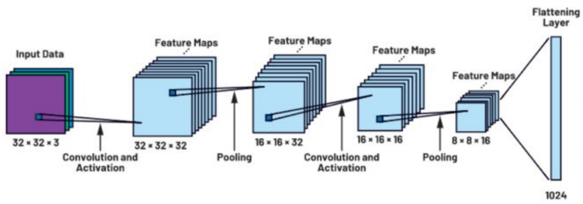

Fig. 1. CNN structure

IV. EXPERIMENTAL SECTION

A. *Dataset*

In this experiment, longitudinal OCTA image data of 5,790 high-myopia patients were collected. Each patient had their images acquired 2 times at different time points, resulting in a total of 11,580 OCTA images. The dataset was partitioned into a training set and a test set at a ratio of 7:3. The training set was employed for model training and parameter adjustment, while the test set was utilized to evaluate the performance of the model. Meanwhile, the images were annotated to mark the presence or absence of choroidal vascular lesions, as well as the type and degree of the lesions.

B. *Experimental Setup*

Model Selection: The CNN was adopted. The network architecture consists of multiple convolutional layers, pooling layers, and fully-connected layers. The convolutional layers utilize convolutional kernels of different sizes to extract multi-scale attributes of the images. The pooling layers employ max-pooling operations to reduce the resolution of the attribute maps, and the fully-connected layers are used for the final classification prediction.

Training Parameters: The Adam optimizer was used, with the learning rate set at 0.001, the batch size set at 32, and the number of training epochs set at 50. During the training process, the cross-entropy loss function was employed to measure the difference between the model's predicted values and the true values, and the model's parameters were updated through the backpropagation algorithm.

Evaluation Metrics: Accuracy, Recall, F1-score, and the Area Under the Receiver Operating Characteristic Curve (AUC-ROC) were used to evaluate the performance of the model. These metrics can comprehensively reflect the accuracy and stability of the model in the classification task.

C. *Experimental Results*

After training and testing, the performance of the model on the test set is shown in Fig. 2.

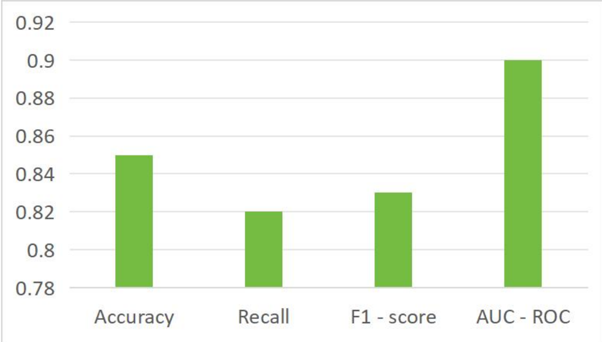

Fig. 2. The performance of the model

As can be seen from the data in the table, the model achieved good performance in the prediction task of choroidal vascular lesions in high myopia, Fig.2. The accuracy reached 0.85, indicating that the model can correctly predict the categories of most samples; the recall rate was 0.82, suggesting that the model can well identify the samples with actual lesions; the F1-score, which comprehensively considers accuracy and recall, was 0.83; the AUC-ROC value was 0.90, further demonstrating that the model has a high discrimination ability and can effectively distinguish between lesioned and non-lesioned samples.

To more intuitively demonstrate the prediction effect of the model on different lesion types, we separately evaluated different types of choroidal vascular lesions, and the results are shown in Table 1:

TABLE I. DIFFERENT LESION TYPES RESULTS

Lesion Types	Accuracy	Recall	F1-score
Type A	0.88	0.85	0.86
Type B	0.82	0.78	0.80
Type C	0.80	0.80	0.80

It can be seen from the above table that the model has a certain prediction ability for different types of choroidal vascular lesions. Among them, the prediction effect for Type A lesions is the best, with relatively high accuracy, recall, and F1-score; for Type B and Type C lesions, although the performance is slightly lower than that of Type A, it can also reach a good prediction level.

D. *Ablation Experiments*

To verify the effectiveness of each component in the model, ablation experiments were carried out. Parts of the structures in the convolutional layers, pooling layers, and fully-connected layers of the model were respectively removed, and then the model was retrained and evaluated on the test set. The results are shown in Table 2:

TABLE II. ABLATION RESULTS

Model Settings	Accuracy	Recall	F1-score	AUC-ROC
Complete Model	0.85	0.82	0.83	0.90
Remove Part of Convolutional Layers	0.78	0.75	0.76	0.85
Remove Part of Pooling Layers	0.82	0.80	0.81	0.88
Remove Part of Fully-	0.80	0.78	0.79	0.86

Connected Layers				

From the results of the ablation experiments, it can be seen that when part of the convolutional layers is removed, all the performance indicators of the model decline significantly. The accuracy drops to 0.78, and the AUC-ROC drops to 0.85, indicating that the convolutional layers play a key role in extracting image attributes. After removing part of the pooling layers, the model performance also declines, but the decline range is relatively small, indicating that the pooling layers help to reduce the computational load and retain important attributes. When part of the fully-connected layers is removed, the model performance also declines, indicating that the fully-connected layers are crucial for the final classification prediction. Through the ablation experiments, the rationality of the model structure design and the effectiveness of each component are further verified.

V. CONCLUSION

This research centered on longitudinal OCTA analysis and data-driven modeling, aiming to overcome the problem of predicting choroidal vascular lesions in high myopia. Through a rigorous experimental process, the convolutional neural network was used to process a large amount of longitudinal OCTA image data, and the constructed prediction model demonstrated excellent performance. In the prediction task, its accuracy was as high as 0.85, and the AUC-ROC reached 0.90. It also showed good prediction effects for different types of lesions. The ablation experiments clearly verified the key roles of the convolutional layers, pooling layers, and fully-connected layers in the attribute extraction, dimensionality reduction, and classification prediction. This research achievement not only provides a new and effective way for the early and accurate prediction of choroidal vascular lesions in high myopia but also offers strong technical support for early clinical intervention, greatly reducing the risk of visual impairment in patients. In the future, plans include further enhancing the model's generalization ability and prediction accuracy by optimizing the model structure and expanding the dataset, with the expectation of playing a greater value in ophthalmic clinical practice and assisting more patients.

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