

Prototype Learning for Visual Field Estimation from Fundus Photography in High Myopia

Guoliang Li¹, Zipei Yan², Zhengji Liu³, Shuai Wang⁴, Rachel Ka-man Chun^{3,5},
Yongjin Zhou¹, Chea-su Kee^{3,5}, and Dong Liang^{3,5}(✉)

¹ School of Biomedical Engineering, Medical School, Shenzhen University, Shenzhen, China

² Department of Electronic Engineering, The Chinese University of Hong Kong, Hong Kong, China

³ School of Optometry, The Hong Kong Polytechnic University, Hong Kong, China

⁴ Data Science and Analytics Thrust, The Hong Kong University of Science and Technology (Guangzhou), Guangzhou, China

⁵ Centre for Eye and Vision Research, 17W Hong Kong Science Park, Hong Kong, China

dong.liang@polyu.edu.hk

Abstract. Visual field (VF) sensitivity assessment is critical for quantifying functional impairment in high myopia (HM), yet conventional perimetry is subjective, time-consuming, and affected by substantial test-retest variability. Deep learning-based estimation of VF sensitivity from fundus photography has emerged as a promising alternative; however, most existing approaches directly regress all 52 pointwise sensitivities and do not explicitly consider latent defect patterns. In this work, we propose ProtoVF, a prototype-based framework for fundus-to-VF estimation in HM. ProtoVF explores the underlying low-dimensional prototypes of VF patterns and predicts their combination coefficients from fundus images to estimate the full 52-point VF sensitivity map. By reformulating VF estimation as a prototype-learning problem, ProtoVF imposes an explicit prior over plausible VF patterns and decomposes predictions into clinically interpretable prototype patterns. In five-fold cross-validation on a large real-world HM cohort, ProtoVF achieved 2.55 MAE and 4.09 RMSE, outperforming the regression baseline, particularly in eyes with severe VF loss ($MD \leq -6$ dB). These findings demonstrate that this prototype-based learning enables a more accurate, robust, and interpretable solution for fundus photography-based VF estimation in HM. Our code is available at <https://github.com/OptometryAI/ProtoVF>.

Keywords: Visual field · Fundus photography · Prototype learning

1 Introduction

High myopia (HM) is a major cause of irreversible visual impairment and a growing public health burden worldwide [8]. Reliable functional assessment is therefore essential for risk stratification and follow-up in HM. Standard automated

perimetry (SAP) remains the clinical reference for visual field (VF) evaluation, yet it is time-consuming, highly dependent on patient cooperation, and vulnerable to test-retest variability [5,24]. These limitations reduce accessibility and consistency of functional assessment in routine HM care.

Retinal imaging offers a practical complementary source of information for HM. Fundus imaging and optical coherence tomography are objective, fast, and widely available for myopia management [16,22]. Prior studies have shown that retinal structure is associated with functional loss patterns [20,23,26], and recent deep learning-based methods have explored VF estimation from retinal images in glaucoma and HM cohorts [1,7,11,13,27,28,29]. These results support the feasibility of imaging-derived functional assessment.

Despite this progress, three methodological gaps still remain. First, many approaches formulate VF estimation as a direct regression of 52 independent points [11,13,29], while VF defects show structured spatial configurations associated with ocular pathology [2,15,21]. Ignoring such latent structure can weaken model robustness and reduce clinical interpretability. Second, VF labels can be noisy and heteroscedastic since perimetric VF testing is subjective, with reduced reliability and stronger floor effects in severe loss regions [9,10,24]. Third, paired fundus-VF data in HM remain limited in current practice [16], increasing the risk of overfitting in the regression of high-dimensional VF.

In summary, these limitations reveal a shared challenge: current models attempt to learn unconstrained high-dimensional VF outputs from limited and noisy labels. We therefore ask whether constraining the prediction space to a compact set of representative VF patterns can enhance robustness while preserving clinically meaningful defect morphology. Our central hypothesis is that VF patterns reside in a low-dimensional, compact manifold that can be explicitly parameterized, yielding greater robustness and interpretability than unconstrained direct regression.

To investigate this hypothesis, we introduce ProtoVF, which distills compact prototypes of representative VF patterns from training VFs, predicts prototype coefficients from fundus images, and reconstructs the full 52-point VF map by combining these prototypes. This formulation transforms high-dimensional pointwise regression into a prototype-coefficient combination by leveraging a structural prior on prototypes, thereby improving robustness and interpretability in a limited, noisy-label regime.

Our contributions are summarized as follows:

- To the best of our knowledge, this is the first study to quantitatively identify and systematically characterize representative VF prototypes in HM using unsupervised decomposition, providing a clinically interpretable basis for describing VF loss patterns.
- We introduce a prototype learning framework, ProtoVF, leveraging compact VF prototypes rather than directly regressing unconstrained independent point predictions, thereby enhancing robustness and interpretability.
- We validate the proposed framework on a large real-world HM cohort with cross-validation, including subgroup analyses relevant to severe VF loss.

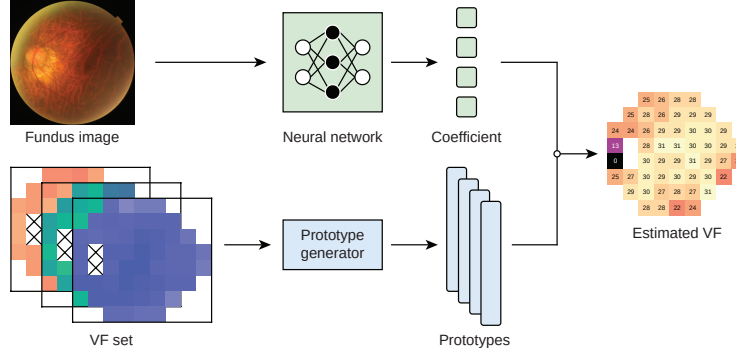


Fig. 1. Overview of the proposed ProtoVF

2 Method

2.1 Problem Definition

Let $\mathcal{Y} = \{\mathbf{y}_i\}_{i=1}^n$ denote a collection of vectorized 24-2 VF measurements, where each $\mathbf{y}_i \in \mathbb{R}^m$ represents the sensitivities at the 52 effective test locations (i.e., $m = 52$). For each VF $\mathbf{y}_i$, we also observe a corresponding color fundus image $\mathbf{x}_i \in \mathbb{R}^l$ in vectorized form. We therefore define the paired training dataset $\mathcal{D}_{\text{train}} = \{(\mathbf{x}_i, \mathbf{y}_i)\}_{i=1}^n$, where each $(\mathbf{x}_i, \mathbf{y}_i)$ is a fundus-VF pair.

Given a fundus image $\mathbf{x}_i$, our objective is to predict the corresponding VF $\hat{\mathbf{y}}_i$ by learning from $\mathcal{D}_{\text{train}}$. This problem poses two principal challenges:

- Data scarcity and output dimensionality: The sample size $|\mathcal{D}_{\text{train}}|$ is typically limited, while the VF output dimension m is substantially large than that in conventional scalar regression tasks, complicating generalization and increasing the risk of overfitting [28].
- Measurement noise and subjectivity: VF testing is inherently subjective and can be influenced by cognitive and physical factors, introducing nontrivial noise into $\mathbf{y}_i$ [5, 24].

Our framework is designed to address both constraints by leveraging the paired structure of $(\mathbf{x}_i, \mathbf{y}_i)$ and explicitly accounting for the high-dimensional, noisy nature of VF measurements.

2.2 Overview of Proposed Method

We provide an overview of the proposed ProtoVF in Fig. 1. ProtoVF addresses the challenges outlined above through the perspective of prototype learning [25]. Rather than directly regressing the target VF $\mathbf{y}_i$ from a given fundus image $\mathbf{x}_i$, ProtoVF represents the prediction as a linear combination of a compact set of

distilled VF prototypes following a basis-approximation formulation [3,19] as:

$$\hat{\mathbf{y}}_i = \mathbf{Z}\boldsymbol{\alpha}_i = \sum_{j=1}^k \alpha_{ij} \cdot \mathbf{z}_j, \quad (1)$$

where $\mathbf{Z} = [\mathbf{z}_1, \mathbf{z}_2, \dots, \mathbf{z}_k] \in \mathbb{R}^{m \times k}$ is the prototype basis matrix distilled from the training VF set $\mathcal{Y}$, with each $\mathbf{z}_j \in \mathbb{R}^m$ being a prototype basis vector, and $\boldsymbol{\alpha}_i \in \mathbb{R}^k$ denotes the prototype coefficients inferred from the corresponding fundus image $\mathbf{x}_i$.

This formulation shifts the learning problem from predicting a high-dimensional VF directly to estimating a low-dimensional coefficient vector associated with VF prototypes. By constraining predictions to the prototype span, ProtoVF reduces the effective output dimensionality and mitigates overfitting in small-sample regimes. It also imposes a structure that is robust to VF measurement noise by leveraging shared patterns captured by the prototypes.

2.3 Prototype Generation for Visual Fields

We generate prototypes directly from the training VF set $\mathcal{Y} = \{\mathbf{y}_i\}_{i=1}^n$. The premise is that pathologic VF loss patterns are not arbitrary but concentrate within a low-dimensional subspace. Consequently, a compact prototype set can capture the principal modes of variation, with $k \ll n$. Formally, we have:

$$\mathcal{Z} = \mathcal{F}_k(\mathcal{Y}), \quad (2)$$

where $\mathcal{F}_k(\cdot)$ denotes a prototype-generation operator producing $\mathcal{Z} = \{\mathbf{z}_j\}_{j=1}^k$.

Importantly, the prototype basis $\mathbf{Z}$ is generated solely from $\mathbf{Y}_{\text{train}}$ in the VF space, without using any fundus information, and is independent of the image encoder. We evaluate several alternatives of $\mathcal{F}_k$, including archetypal analysis (AA) [4], principal component analysis (PCA) [14], nonnegative matrix factorization (NMF) [18], and truncated singular value decomposition (Truncated SVD) [6]. For each method, we retain the top- k components to form the prototype set $\mathcal{Z}$ and construct the prototype matrix $\mathbf{Z}$ used in (1). We conducted an ablation study to examine different generation functions; based on the results, we adopt PCA as the default $\mathcal{F}_k$ in our framework. Additional details and comparative results are provided in the experimental section.

2.4 Coefficient Parameterization from Fundus Image

For each fundus image $\mathbf{x}_i$, we infer the prototype coefficient $\boldsymbol{\alpha}_i$ using a neural network:

$$\boldsymbol{\alpha}_i = \mathbf{g}_{\boldsymbol{\theta}}(\mathbf{x}_i), \quad (3)$$

where $\mathbf{g}_{\boldsymbol{\theta}}(\cdot)$ denotes the neural network with its learnable parameters $\boldsymbol{\theta}$.

Table 1. Five-fold cross-validation performance. Mean $\pm$ STD are computed across folds for each criterion. n denotes the number of data points. Better results are **bold-faced**.

Method	MAE ($\downarrow$)	RMSE ($\downarrow$)	PCC ($\uparrow$)	SMAPE ($\downarrow$)
<i>Overall performance ($n = 1,688$)</i>				
Regression	2.668 ± 0.153	4.224 ± 0.333	0.430 ± 0.071	11.143 ± 0.733
ProtoVF (AA)	2.566 ± 0.146	4.164 ± 0.352	0.445 ± 0.084	10.825 ± 0.724
ProtoVF (NMF)	2.640 ± 0.194	4.259 ± 0.400	0.426 ± 0.094	10.996 ± 0.902
ProtoVF (PCA)	2.551 ± 0.099	4.089 ± 0.295	0.476 ± 0.064	10.788 ± 0.545
<i>Subgroup performance for none-to-mild loss (MD > -6 dB, $n = 1,507$)</i>				
Regression	2.338 ± 0.065	3.391 ± 0.060	0.438 ± 0.028	8.964 ± 0.178
ProtoVF (AA)	2.200 ± 0.056	3.271 ± 0.091	0.463 ± 0.050	8.493 ± 0.209
ProtoVF (NMF)	2.263 ± 0.109	3.334 ± 0.139	0.445 ± 0.060	8.665 ± 0.456
ProtoVF (PCA)	2.231 ± 0.081	3.257 ± 0.120	0.483 ± 0.033	8.630 ± 0.341
<i>Subgroup performance for moderate-to-severe loss (MD $\leq$ -6 dB, $n = 181$)</i>				
Regression	5.498 ± 1.397	8.412 ± 1.823	0.348 ± 0.080	29.744 ± 7.901
ProtoVF (AA)	5.659 ± 1.168	8.526 ± 1.755	0.339 ± 0.074	30.525 ± 6.812
ProtoVF (NMF)	5.811 ± 1.387	8.745 ± 1.875	0.301 ± 0.097	30.677 ± 7.618
ProtoVF (PCA)	5.303 ± 1.242	8.222 ± 1.851	0.327 ± 0.082	29.223 ± 7.227

We optimize the network’s parameters θ by minimizing the reconstruction error between the ground-truth VF and its prototype-based approximation as follows:

$$\mathcal{L}(\theta) = \sum_{i=1}^n \|y_i - \hat{y}_i\|_2^2 = \sum_{i=1}^n \|y_i - Zg_{\theta}(x_i)\|_2^2, \quad (4)$$

where $\|\cdot\|_2$ denotes the ℓ_2 norm.

For clarity, we summarize the training and inference steps of ProtoVF below.
Training. Given a training set $\mathcal{D}_{\text{train}} = \{(x_i, y_i)\}_{i=1}^n$:

1. Generate a prototype basis Z from $\{y_i\}_{i=1}^n$ using a prototype-generation operator $\mathcal{F}_k$ in (2), e.g., PCA, AA, NMF, or truncated SVD.
2. Randomly initialize the fundus image encoder $g_{\theta}(\cdot)$, which maps each fundus image x_i to a coefficient vector $\alpha_i = g_{\theta}(x_i)$.
3. Reconstruct the VF prediction as $\hat{y}_i = Z\alpha_i$.
4. Optimize the encoder weight θ by minimizing (4) while keeping Z fixed.

Inference. Given a test fundus image x :

1. Predict prototype coefficients $\alpha = g_{\theta}(x)$ using the trained encoder.
2. Reconstruct the VF estimate as $\hat{y} = Z\alpha$ using the fixed prototype basis.

3 Experiment

3.1 The Studied Data

Data acquisition. We collected paired fundus photographs and VF data from a HM cohort at a clinical center. The dataset comprised 1,688 eyes with matched

fundus-VF pairs. Fundus photography was acquired using a Topcon fundus camera centered on the fovea. VF testing was performed using the Humphrey Field Analyzer with the SITA Standard 24-2 protocol, yielding threshold sensitivity (dB) at 52 test locations after excluding the physiological blind spot.

Data preprocessing. To ensure consistent laterality, we used the right-eye configuration as the reference, and horizontally flipped fundus photographs and corresponding VF maps from left eyes to match this orientation.

3.2 Experimental Setup

Evaluation methods. We adopted subject-level five-fold cross-validation, stratified by age and MD severity. Splitting was performed at the subject level to ensure that eyes from the same patient did not appear in both training and validation folds. Model performance was evaluated quantitatively using mean absolute error (MAE), root-mean-square error (RMSE), and symmetric mean absolute percentage error (SMAPE). In addition, we computed the Pearson correlation coefficient (PCC) to assess the linear agreement between predicted and measured VF sensitivities. We further performed subgroup analysis according to VF loss severity, including none-to-mild loss ($MD > -6.0$ dB) *vs.* moderate-to-severe loss ($MD \leq -6.0$ dB). Statistical significance was assessed using paired t-tests between ProtoVF and the regression baseline on held-out predictions across the five cross-validation folds.

Implementation details. We used the ResNet-34 [12] as the backbone in our experiments, which is widely used in medical image analysis to ensure fair comparison with prior work. We compare ProtoVF against conventional regression and ablations with different prototypes. In the main configuration, we set the number of prototypes to $k = 10$ in our framework and used PCA for prototype generation, where PCA is applied to centered VF data from preprocessing. All models are trained for 200 epochs using the Adam optimizer [17] with a batch size of 8, a learning rate of 10^{-4} , momentum of 0.9, and weight decay of 10^{-4} .

3.3 Experimental Results

Main results. Table 1 summarizes the performance of ProtoVF and the regression baseline across five-fold cross-validation. Overall, the prototype-based models consistently outperformed the regression baseline across most evaluation metrics, suggesting that approximating VF patterns using data-driven prototypes is beneficial. Among all ProtoVF variants, ProtoVF (PCA) achieved the best performance, improving MAE and RMSE by 4.4% and 3.2%, respectively, compared with the regression baseline (both $p < 0.05$).

Subgroup results. Table 1 further reports subgroup performance stratified by perimetric MD as an indicator of VF loss severity. In the none-to-mild subgroup, all ProtoVF variants reduced predictive errors relative to the regression baseline. In the moderate-to-severe subgroup, ProtoVF (PCA) achieved the best MAE, RMSE, and SMAPE, indicating that the PCA-based prototype constraint was most beneficial in eyes with more severe VF loss.

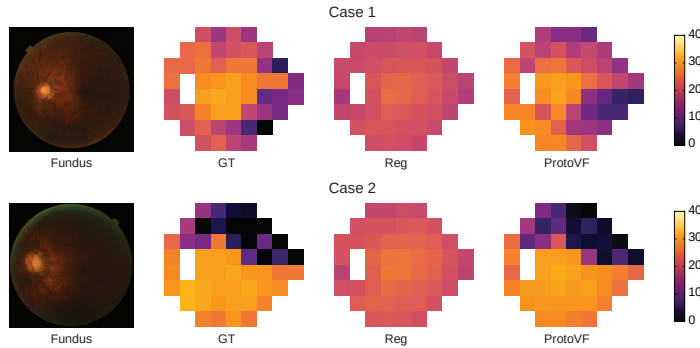


Fig. 2. Visualization of estimated VF on two representative cases. GT denotes the ground-truth, and Reg denotes the regression baseline.

Visualization of predictions. Fig. 2 presents qualitative examples from two representative cases. In both cases, the regression baseline generated overly similar predictions and failed to adequately capture localized VF loss patterns. In contrast, ProtoVF yielded more accurate and informative predictions, with improved localization of VF defects and more clinically interpretable spatial patterns, which may facilitate improved HM management in future practice.

3.4 Ablation Study

Fig. 3 shows the reconstruction error as a function of the number of prototypes for different prototype generation methods. As expected, the reconstruction error generally decreased as the number of prototypes increased for most methods, while the AA-based approach showed an increase in validation reconstruction error when the number of prototypes became large, suggesting potential overfitting. However, Fig. 3 reflects VF reconstruction quality rather than final fundus-to-VF prediction accuracy. Based on the overall reconstruction performance and model simplicity, we selected $k = 10$ prototypes for subsequent experiments, as this configuration provided a favorable balance between representational capacity and generalization, while larger k may increase coefficient-learning complexity and amplify VF label noise.

3.5 Prototypes Visualization

Fig. 3 also shows the visualization of the generated prototypes using AA. Although PCA was used in the main ProtoVF model due to its superior predictive performance, we visualize AA-derived prototypes because archetypes correspond to representative VF patterns near the boundary of the data distribution and are therefore more clinically interpretable. Similar to other prototype generation methods, AA generates prototypes as convex combinations of observed

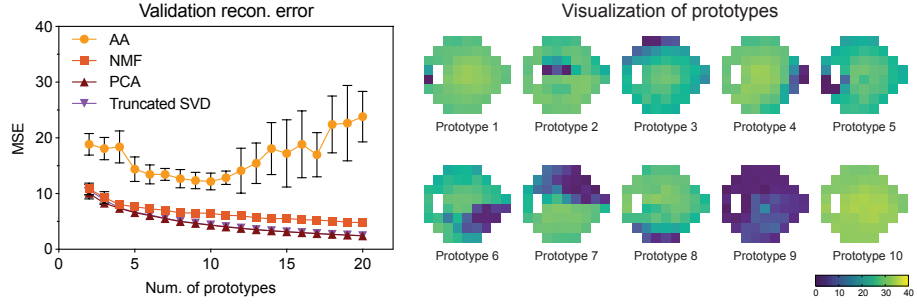


Fig. 3. Left: validation VF reconstruction error with different numbers of prototypes and prototype-generation methods. Right: visualization of AA-generated prototypes.

VFs, which typically lie near the boundary of the data distribution and emphasize distinctive structural patterns. Each prototype can be interpreted as a low-dimensional representation of a characteristic VF loss pattern, and each VF measurement can in turn be approximated as a weighted combination of all prototypes. This formulation reduces the complexity of VF estimation while preserving clinically meaningful spatial patterns. Qualitatively, several prototypes resembled known VF defect patterns relevant to high myopia and related optic neuropathies. For example, prototypes 1 and 5 appeared to reflect enlargement of the blind spot, prototype 7 resembled an arcuate-like defect, and prototype 4 exhibited a nasal-step-like pattern. These observations suggest that the learned prototypes capture interpretable structural priors that may facilitate more robust and clinically meaningful VF estimation.

4 Conclusion

In this work, we propose ProtoVF, a prototype learning framework for VF estimation from fundus photography in high myopia. By reformulating unconstrained direct 52-point regression as prototype-coefficient prediction in a compact prototype VF space, ProtoVF enables structured output prediction and a clinically meaningful basis approximation of VF loss. Evaluated on a large real-world HM dataset, ProtoVF outperforms conventional regression, particularly in eyes with advanced VF loss. These findings highlight the potential of prototype learning to support imaging-derived functional assessment in high myopia and may facilitate more accessible, scalable, and clinically informative evaluation of vision impairment, particularly for preliminary screening and risk assessment. A limitation of this work is that the study was conducted on a single-center, single-camera HM cohort with a relatively homogeneous population and imaging protocol, which may introduce domain shifts under external clinical settings. In particular, the learned prototype space may be sensitive to variations in data distribution across centers. Future work will evaluate ProtoVF on multi-center datasets to assess its cross-domain robustness.

Acknowledgements. This work was supported by the InnoHK initiative of the Innovation and Technology Commission of the Hong Kong Special Administrative Region Government; the PolyU internal grants (P0035514, P0055266), RMGS (P0045696), RCSV (P0057911), The Hong Kong Polytechnic University, Hong Kong; and the Medical-Engineering Interdisciplinary Research Foundation of Shenzhen University (00000326), Shenzhen, China.

Disclosure of Interests. The authors have no competing interests to declare that are relevant to the content of this article.

References

1. Asaoka, R., Xu, L., Murata, H., Kiwaki, T., Matsuura, M., Fujino, Y., Tanito, M., Mori, K., Ikeda, Y., Kanamoto, T., et al.: A joint multitask learning model for cross-sectional and longitudinal predictions of visual field using oct. *Ophthalmol. Sci.* **1**(4), 100055 (2021)
2. Banc, A., Kedar, S.: Interpretation of the visual field in neuro-ophthalmic disorders. *Curr. Neurol. Neurosci. Rep.* **24**(3), 67–81 (2024)
3. Blu, T., Luisier, F.: The SURE-LET approach to image denoising. *IEEE Trans. Image Process.* **16**(11), 2778–2786 (2007)
4. Cutler, A., Breiman, L.: Archetypal analysis. *Technometrics* **36**(4), 338–347 (1994)
5. Delgado, M.F., Nguyen, N.T., Cox, T.A., Singh, K., Lee, D.A., Dueker, D.K., Fechtner, R.D., Juzych, M.S., Lin, S.C., Netland, P.A., et al.: Automated perimetry: a report by the american academy of ophthalmology. *Ophthalmology* **109**(12), 2362–2374 (2002)
6. Eckart, C., Young, G.: The approximation of one matrix by another of lower rank. *Psychometrika* **1**(3), 211–218 (1936)
7. Eslami, M., Kim, J.A., Zhang, M., Boland, M.V., Wang, M., Chang, D.S., Elze, T.: Visual field prediction: evaluating the clinical relevance of deep learning models. *Ophthalmol. Sci.* **3**(1), 100222 (2023)
8. Fricke, T.R., Jong, M., Naidoo, K.S., Sankaridurg, P., Naduvilath, T.J., Ho, S.M., Wong, T.Y., Resnikoff, S.: Global prevalence of visual impairment associated with myopic macular degeneration and temporal trends from 2000 through 2050: systematic review, meta-analysis and modelling. *Br. J. Ophthalmol.* **102**(7), 855–862 (2018)
9. Gardiner, S.K., Swanson, W.H., Demirel, S.: The effect of limiting the range of perimetric sensitivities on pointwise assessment of visual field progression in glaucoma. *Investig. Ophthalmol. & Vis. Sci.* **57**(1), 288–294 (2016)
10. Gardiner, S.K., Swanson, W.H., Goren, D., Mansberger, S.L., Demirel, S.: Assessment of the reliability of standard automated perimetry in regions of glaucomatous damage. *Ophthalmology* **121**(7), 1359–1369 (2014)
11. Guo, Z., Kwon, Y.H., Lee, K., Wang, K., Wahle, A., Alward, W.L., Fingert, J.H., Bettis, D.I., Johnson, C.A., Garvin, M.K., et al.: Optical coherence tomography analysis based prediction of humphrey 24-2 visual field thresholds in patients with glaucoma. *Investig. Ophthalmol. & Vis. Sci.* **58**(10), 3975–3985 (2017)
12. He, K., Zhang, X., Ren, S., Sun, J.: Deep residual learning for image recognition. In: *CVPR*. pp. 770–778 (2016)

13. Hemelings, R., Elen, B., Barbosa-Breda, J., Bellon, E., Blaschko, M.B., De Boever, P., Stalmans, I.: Pointwise visual field estimation from optical coherence tomography in glaucoma using deep learning. *Transl. Vis. Sci. & Technol.* **11**(8), 22–22 (2022)
14. Hotelling, H.: Analysis of a complex of statistical variables into principal components. *J. Educ. Psychol.* **24**(6), 417 (1933)
15. Jiang, J., Song, Y., Kong, K., Wang, P., Lin, F., Gao, X., Wang, Z., Jin, L., Chen, M., Lam, D.S., et al.: Optic nerve head abnormalities in nonpathologic high myopia and the relationship with visual field. *Asia-Pac. J. Ophthalmol.* **12**(5), 460–467 (2023)
16. Jones, D., Chow, A., Fadel, D., Meijome, J.M.G., Grzybowski, A., Kollbaum, P., Loughman, J., Wolffsohn, J.: Imi—instrumentation for myopia management. *Investig. Ophthalmol. & Vis. Sci.* **66**(9), 7–7 (2025)
17. Kingma, D.P., Ba, J.: Adam: A method for stochastic optimization. In: *ICLR* (2015)
18. Lee, D.D., Seung, H.S.: Learning the parts of objects by non-negative matrix factorization. *Nature* **401**(6755), 788–791 (1999)
19. Li, J., Luisier, F., Blu, T.: PURE-LET image deconvolution. *IEEE Trans. Image Process.* **27**(1), 92–105 (2017)
20. Liang, D., Leung, T.W., Kee, C.S.: Measuring retinal thickness and visual acuity in eyes with different types of astigmatism in a cohort of hong kong chinese adults. *Investig. Ophthalmol. & Vis. Sci.* **64**(1), 2–2 (2023)
21. Lin, F., Chen, S., Song, Y., Li, F., Wang, W., Zhao, Z., Gao, X., Wang, P., Jin, L., Liu, Y., et al.: Classification of visual field abnormalities in highly myopic eyes without pathologic change. *Ophthalmology* **129**(7), 803–812 (2022)
22. Liu, Z., Law, T.K., Li, J., To, C.H., Chun, R.K.M.: Self-supervised denoising of optical coherence tomography with inter-frame representation. In: *2023 IEEE International Conference on Image Processing (ICIP)*. pp. 3334–3338. IEEE (2023)
23. Park, H.Y.L., Kim, Y.C., Jung, Y., Park, C.K.: Vertical disc tilt and features of the optic nerve head anatomy are related to visual field defect in myopic eyes. *Sci. Rep.* **9**(1), 3485 (2019)
24. Phu, J., Khuu, S.K., Nivison-Smith, L., Kalloniatis, M.: Standard automated perimetry for glaucoma and diseases of the retina and visual pathways: Current and future perspectives. *Prog. Retin. Eye Res.* **104**, 101307 (2025)
25. Wang, S., Yan, Z., Zhang, D., Wei, H., Li, Z., Li, R.: Prototype knowledge distillation for medical segmentation with missing modality. In: *ICASSP*. pp. 1–5. IEEE (2023)
26. Xie, S., Kamoi, K., Igarashi-Yokoi, T., Uramoto, K., Takahashi, H., Nakao, N., Ohno-Matsui, K.: Structural abnormalities in the papillary and peripapillary areas and corresponding visual field defects in eyes with pathologic myopia. *Investig. Ophthalmol. & Vis. Sci.* **63**(4), 13–13 (2022)
27. Xu, L., Asaoka, R., Kiwaki, T., Murata, H., Fujino, Y., Matsuura, M., Hashimoto, Y., Asano, S., Miki, A., Mori, K., et al.: Predicting the glaucomatous central 10-degree visual field from optical coherence tomography using deep learning and tensor regression. *Am. J. Ophthalmol.* **218**, 304–313 (2020)
28. Yan, Z., Liang, D., Xu, L., Li, J., Liu, Z., Wang, S., Cao, J., Kee, C.s.: VF-HM: Vision loss estimation using fundus photograph for high myopia. In: *MICCAI*. pp. 649–659. Springer (2023)
29. Yan, Z., Liang, Z., Liu, Z., Wang, S., Chun, R.K.M., Li, J., Kee, C.s., Liang, D.: Generalized robust fundus photography-based vision loss estimation for high myopia. In: *MICCAI*. pp. 700–710. Springer (2024)