

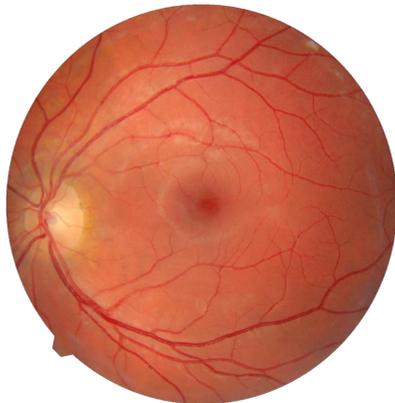
# Prediction of Optical Coherence Tomography Retinal Layer Thickness from Colour Fundus Photography in the UK Biobank

James C Porter; Miguel O. Bernabeu; Baljean Dhillon

Abstract  
# 429194

## 1. Background

- **Retinal thicknesses** such as RNFL are important biomarkers for neurodegenerative disease<sup>1</sup> but require expensive and large **Optical Coherence Tomography (OCT)** machines to image them.
- **Colour Fundus Photography (CFP)** is ubiquitous, cheap, simple and has historic data.
- **We investigate predicting retinal thicknesses using Ridge regression on deep CFP embeddings.** This could enable large-scale screening for neurodegenerative disease like Alzheimer's.



## 2. Data

We used paired CFP images and OCT-derived mRNFL, mGCIPL and mINL thicknesses from the **UK Biobank**. We retained **102,232 eyes** after quality control filtering CFPs via QuickQual<sup>2</sup>  $p(\text{bad}) \geq 0.9$  for CFP and OCTs via Topcon TABS quality metrics (Q-factor  $\leq 45$  & worst 20% across other).

Features were extracted **pre-trained RETfound** foundation model<sup>3</sup> embeddings and image statistics (e.g. RGB variance).

## 3. Methods

We trained separate **ridge regression** (10-CV) models to predict **mRNFL, mGCIPL and mINL** using subsets of the data to investigate their effects on prediction: eye laterality, sex, ethnicity, systemic-health.

'Healthcare system interaction score' (HS) is a simple proxy for systemic-health, with a higher value for worse health. Calculated via: ICD-10 count (D), medication count (M), baseline age ( $A_0$ ), death age ( $A_d$ ), prior cancer (C), Age factor (AF) & Death factor (DF).

$$AF = 1 - \frac{A_0 - \min(A_0)}{\max(A_0) - \min(A_0)} \quad DF = 1 - \frac{(A_d - A_0) - \min(A_d - A_0)}{\max(A_d - A_0) - \min(A_d - A_0)}$$

$$HS = AF(D + 0.5M + C) + DF$$

## 4. Results

Layer	Comparison	$R^2$	MAE [ $\mu\text{m}$ ]	MAE $\Delta$ [ $\mu\text{m}$ ]	p(ttest)	Cohen's d
RNFL	Left / Right	0.231 / 0.303	3.03 / 3.31	-0.28	<0.01	-0.06
	Female / Male	0.244 / 0.270	3.35 / 3.11	0.24	<0.01	0.06
	White / NonWhite	0.283 / 0.232	3.22 / 3.41	-0.19	0.054	-0.04
GCIPL	Left / Right	0.196 / 0.20	4.22 / 4.14	0.08	0.41	0.01
	Female / Male	0.223 / 0.215	4.14 / 4.29	-0.15	0.09	-0.02
	White / NonWhite	0.203 / 0.236	4.20 / 4.32	-0.12	0.29	-0.02
INL	Left / Right	0.090 / 0.105	1.94 / 1.86	0.09	<b>0.037</b>	0.03
	Female / Male	0.089 / 0.079	1.91 / 1.97	-0.06	0.12	-0.02
	White / NonWhite	0.085 / 0.083	1.95 / 1.86	0.10	<b>0.048</b>	0.03

All models had positive  $R^2$  (0.08–0.30) and had MAE 1.9–4.3 $\mu\text{m}$ . This meant that the prediction errors (within 0.02–0.3 $\mu\text{m}$ ) were **comparable to the natural variability in OCT-measured values.**

- **GCIPL** predictions were robust across all strata (no significant  $\Delta\text{MAE}$ )
- **RNFL** predictions were best performing and **INL** the worst.
- **Sex** and **eye laterality** had a significant effect on RNFL predictions but only small effect sizes.
- All **effect sizes** were small (Cohen's  $d < 0.1$ ), therefore models were robust to strata and HS.

Layer	Subset	MAE $\Delta$ [ $\mu\text{m}$ ]	p (t-test)	Cohen's d
GCIPL (left)	HS50	-0.02	0.41	-0.03
	HS60	-0.01	0.57	-0.02
	HS70	0.01	0.69	0.01
	HS80	0.00	0.95	0.00
GCIPL (right)	HS50	-0.03	0.35	-0.03
	HS60	-0.02	0.48	-0.02
	HS70	<b>-0.04</b>	<b>0.026</b>	-0.06
	HS80	0.02	0.32	0.03
INL (left)	HS50	0.00	0.97	0.00
	HS60	0.01	0.50	0.02
	HS70	0.00	0.82	0.01
	HS80	-0.01	0.25	-0.03
INL (right)	HS50	<b>-0.03</b>	<b>0.015</b>	-0.08
	HS60	-0.01	0.10	-0.05
	HS70	-0.01	0.24	-0.03
	HS80	0.01	0.29	0.03
RNFL (left)	HS50	<b>-0.10</b>	<b>&lt;0.001</b>	-0.13
	HS60	-0.03	0.10	-0.05
	HS70	0.00	0.97	0.00
	HS80	-0.02	0.07	-0.04
RNFL (right)	HS50	<b>-0.06</b>	<b>0.015</b>	-0.08
	HS60	-0.01	0.51	-0.02
	HS70	-0.03	0.053	-0.05
	HS80	0.01	0.63	0.01

**HS filtering** did not significantly affect performance. Even at the strictest HS filter, removing the top 50% of highest scores only improved results by 0.03–0.10  $\mu\text{m}$  MAE. Therefore, models were robust to variations in systemic health.

## 5. Conclusions

**Limitations:** single-centre (UKB); linear model may overlook nonlinear features; HS is crude.

**Future:** integrate deep neural networks; validate on non-UKB data; explore longitudinal CFP changes; extend to other retinal layers; improve HS to be more nuanced.

### Take-Home Message:

Ridge regression on CFP achieves MAE comparable to OCT variability for mRNFL, mGCIPL and mINL, and is robust to eye laterality, sex, ethnicity and a systemic-health proxy.