A Appendix

A.1 Non-Contrastive VicReg Loss

VICReg loss with *invariance*, *variance*, and *covariance* terms, is as follows:

$$\begin{aligned} \ell_{\text{contr}}(Z_t, Z_{t+\Delta t}) &= \lambda_S \cdot S(Z_t, Z_{t+\Delta t}) + \lambda_V \cdot (V(Z_t) + V(Z_{t+\Delta t})) \\ &\quad + \lambda_C \cdot (C(Z_t) + C(Z_{t+\Delta t})) \\ S(Z, Z') &= \frac{1}{n}\sum_i \|z_i - z'_i\|_2^2 \quad V(Z) = \frac{1}{d}\sum_{j=1}^{d} max(0, 1 - \text{std}(z^j, \epsilon)) \\ C(Z) &= \frac{1}{d}\sum_{i\neq j}[Cov(Z)]_{i,j}^2, \\ \text{where} \quad Cov(Z) &= \frac{1}{n-1}\sum_{i=1}^{n}(z_i - \bar{z})(z_i - \bar{z})^T. \end{aligned} \tag{6}$$

λ_S, λ_V, and λ_C are set to 15, 25, 5 to bring their magnitude in the same range.

A.2 Derivation of Displacement Map Regularization Term

The pairwise RankNet [4] loss is based on cross-entropy loss for calculating the score-based ranking a pair of elements. Let f be a scoring function for the items x_i and x_j, such that their respective scores are $s_i = f(x_i)$ and $s_j = f(x_j)$. Concordantly the score difference is defined as $s_{ij} = s_i - s_j$. Then, the probability of ranking x_i greater than x_j is defined using the logistic function:

$$\mathcal{P}_{ij} = \frac{e^{s_{ij}}}{1 + e^{s_{ij}}} = \frac{1}{1 + e^{-s_{ij}}} \tag{7}$$

When ranking the items, there are 3 values for ground truth Y; 1 when x_i has higher rank than x_j, 0 when the relation is reversed, and $\frac{1}{2}$ when both items have the same rank. Accordingly, cross-entropy loss for correctly ranking the items is:

$$\mathcal{L}_{ce} = -Y \cdot \log(\mathcal{P}_{ij}) - (1 - Y) \cdot \log(1 - \mathcal{P}_{ij}) \tag{8}$$

In TC, s_i becomes $r_{t+\Delta t}$ and s_j becomes r_t, hence s_{ij} is the DM. For the cross-entropy loss, we implemented s_{ij} as the norm of the DM. Also the ranking class is always 1 because the time difference is kept positive, thus the Eq. 8 becomes:

$$\begin{aligned} \mathcal{L}_{reg} &= -1 \cdot \log(\mathcal{P}_{ij}) - (0) \cdot \log(1 - \mathcal{P}_{ij}) = -\log\left(\frac{1}{1 + e^{-s_{ij}}}\right) \\ &= \log(1 + e^{-s_{ij}}) = \log\left(1 + \exp(-||\rho_\psi(r_t, \Delta t)||_2)\right) \end{aligned} \tag{9}$$

Table 2. Contrastive Augmentations and OCT Details

Contrastive Transformations	**Parameter**
Random Crop & Resize (percentage)	0.4 - 0.8
Random Horizontal Flip (probability)	0.5
Random Color Jittering (probability	0.8
Random Gaussian Blur (kernel size)	21
Random Solarize (threshold)	0.5
Random Rotation (degrees)	± 5
Random Translation (percentage)	± 0.05
Input Time Difference	1-12 Months
Normalization Mean & std	(0.202, 0.113)
OCT Scanner	Cirrus OCT
Resolution	$6 \times 6 \times 2$ mm^3
Projector MLP dimensions	4096-4096-4096
Predictor ρ_ψ MLP dimensions	2049-2048
GPU Used	Nvidia A100 80GB

Table 3. Computational Costs of Each Model

Model	**Batch Update (Seconds)**	**# Trainable Parameters**
VICReg	9.3	65.4M
ESSL	16.3	78.0M
AugSelf	14.2	78.0M
EquiMod	12.6	124.2M
TC	10.4	82.2M

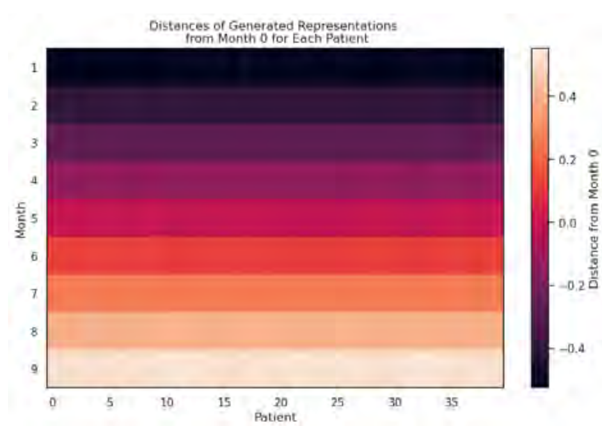

Fig. 3. Distance rankings between the original reprensentation r_0 and its propoageted prediction $r'_{t+\Delta t}$ for 9 consecutive months for 40 patients.