LEARNING REPRESENTATIONS BY PREDICTING THE FUTURE

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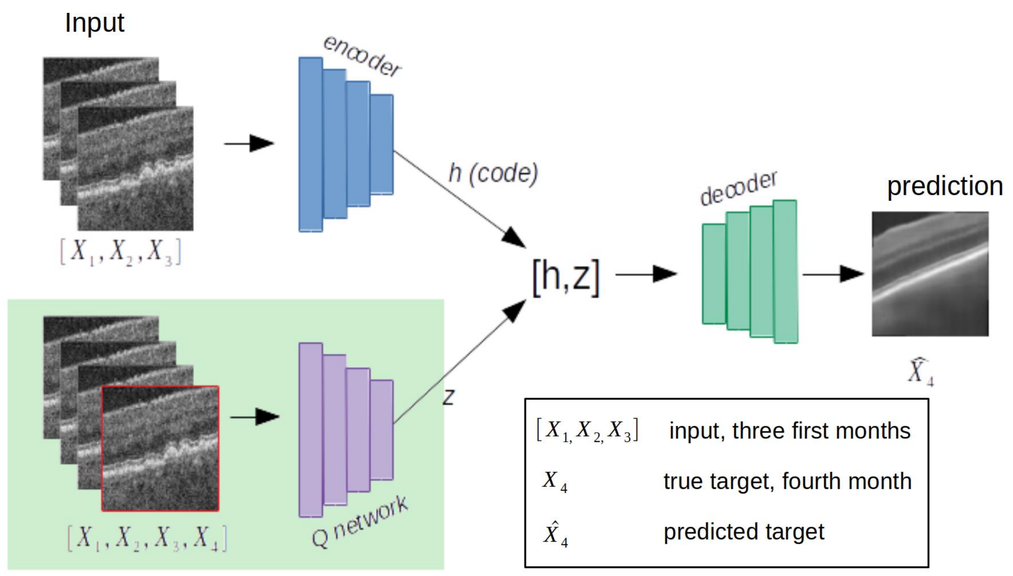
Abstract

Longitudinal imaging displays the static anatomical structures and the dynamic changes of the morphology due to aging or disease progression. We aim at capturing these structures and their evolution in a compact representation to improve the understanding of pathologies and to forecast them. We adapted an unsupervised deep learning framework (CVAE) to learn these structures. Initial evaluation shows that learned representations allow to improve the prediction of morphologic abnormalities.

Methodology

1. Theory

We adapted a **Conditional Variational Autoencoder [1]** . The input vector is three consecutive scans, the target is the next unseen observation.
Autoencoder structure provides compact representations (*h* code), Variational properties makes it more robust to noise and uncertainty of time prediction.



TRAINING TIME

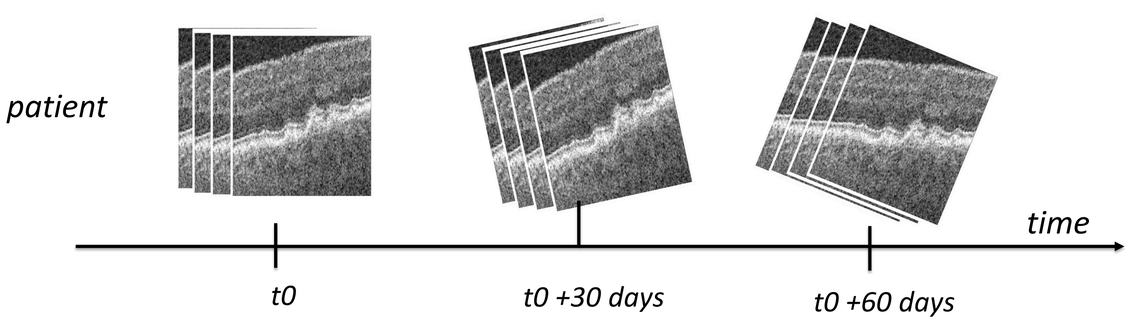
2. Training

Controlled by reconstruction loss on Validation set.

Dataset

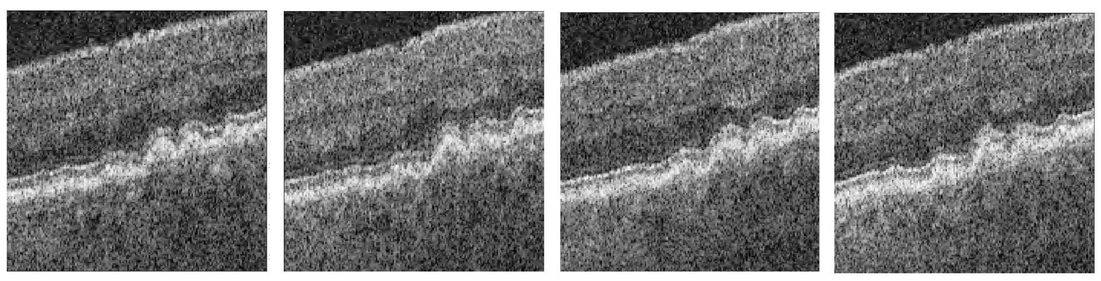
1. Original Data

OCT scans from 204 patients with early stage of **dry AMD** (117 in train, 42 in validation and 45 in test set)
Maximal period of observation: 24 months (monthly follow-up visits)



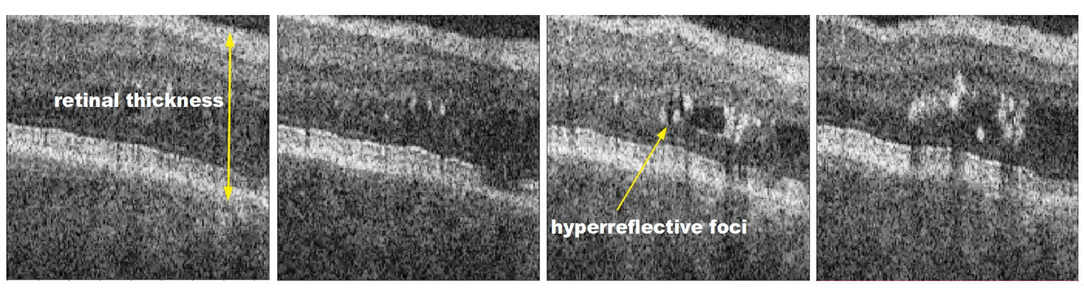
2. Preprocessing

The volumes of each patients are first **registered** (using [2])**,** then smaller patches are cropped from each B-scan.
Final format: every sample is composed from 4 consecutive patches, 170 x 170



Experiments

To evaluate the representations provided by the encoder, we use them as input to predict morphological properties. We chose average **retinal thickness**, average **drusen thickness**, and average **hyperreflective foci** probability (HRF computed with [3]).



Results

R2 score, Mean Absolute Error (MAE) and Mean Squared Error (MSE) on the test set. **Input vector for direct method**: values of the property to predict for the three previous months. **Input for mixed method:** previous values and learned code.

Retinal Thickness	R2	MAE	MSE
Direct	**0.956 +/- 0.005**	**0.154 +/- 0.009**	**0.044 +/- 0.005**
Mixed	0.937 +/- 0.005	0.193 +/- 0.009	0.062 +/- 0.005

Drusen	R2	MAE	MSE
Direct	0.956 +/- 0.009	0.185+/- 0.005	0.148 +/- 0.03
Mixed	**0.971 +/- 0.005**	**0.167 +/- 0.019**	**0.097 +/- 0.016**

HRF	R2	MAE	MSE
Direct	0.820 +/- 0.008	**0.340 +/- 0.010**	0.794 +/- 0.036
Mixed	**0.821 +/- 0.005**	0.390 +/- 0.007	**0.792 +/- 0.023**

The regression performance decreased with the learned representation for the **retinal thickness.** This property is probably too stable and therefore is easy to predict with the direct method. For the **Drusen**, the learned representation clearly improves the results. For the **HRF**, there is no clear improvement.
The interval between the last image and the predicted property (30 days) is probably too short to observe important changes, it will be increased in future experiments.

Conclusion

- Learned representation allows improvement for drusen regression
- Limited dataset: **prediction interval** between last input and prediction is too short

Future work

- Build new dataset with **longer intervals**
- Develop new evaluations on local abnormalities to predict AMD development
- Explore other deep learning framework
  - Adapted to sequence (**recurrent**)
  - With **Adversarial** Losses (to avoid L2 Norm)

References

[1] Kingma D. P. and Welling M. . Auto-encoding variational bayes. URL http://arxiv.org/abs/1312.6114.

[2] Vogl W. D., Waldstein S. M., Gerendas B. S., Schmidt-Erfurth U., and Langs G.. Predicting macular edema recurrence from spatio-temporal signatures in optical coherence tomography images. IEEE Transactions on Medical Imaging, 36(9):1773–1783, Sept 2017.

[3] Schlegl T., Waldstein S. M., Bogunovic H., Endstraßer F., Sadeghipour A., Philip A. M., Podkowinski D., Gerendas B. S., Langs G., and Schmidt-Erfurth U. . Fully automated detection and quantification of macular fluid in oct using deep learning. Ophthalmology, 2017.