

Fundus Image Toolbox: A Python package for fundus image processing

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Summary

The Fundus Image Toolbox is an open source Python suite of tools for working with retinal fundus images. It includes quality prediction, fovea and optic disc center localization, blood vessel segmentation, image registration, and fundus cropping functions. It also provides a collection of useful utilities for image manipulation and image-based PyTorch models. The toolbox is designed to be flexible and easy to use, thus helping to speed up research workflows. It is available as a PyPI package and at https://github.com/berenslab/fundus_image_toolbox.

Statement of need

In ophthalmic research, retinal fundus images are often used as a resource for studying various eye diseases such as diabetic retinopathy, glaucoma and age-related macular degeneration. Consequently, there is a large amount of research on machine learning for fundus image analysis. However, many of the works do not publish their source code, and very few of them provide ready-to-use open source preprocessing tools to the community.

The Fundus Image Toolbox was developed to address this need within the medical image analysis community. It offers a comprehensive set of tools for automated processing of retinal fundus images, covering a wide range of tasks (see Tools). The methods accept paths to images, standard image types (e.g., images loaded with Pillow, OpenCV, or Matplotlib) and batches thereof and where possible, image batches are efficiently processed as such. This allows the tools to be seamlessly combined into a processing pipeline. The quality prediction and localization models have been developed by the authors and allow for both prediction and retraining, while the other main functionalities are based on state-of-the-art methods from the literature that are applicable for inference. By providing an interface for these tasks, the toolbox facilitates the development of new algorithms and models in the field of fundus image analysis. AutoMorph is the closest related work (Zhou et al., 2022), which provides a distinct and smaller set of tools for fundus image processing.

Tools

The main functionalities of the Fundus Image Toolbox are:

- Quality prediction (Figure 1a). We trained an ensemble of ResNets and EfficientNets on the combined DeepDRiD and DrimDB datasets (R. Liu et al., 2022; Sevik et al., 2014) to predict the gradeability of fundus images. The datasets are publicly available and comprise images of retinas with diabetic retinopathy, healthy retinas and outliers such as outer eye images. The model ensemble achieved an accuracy of 0.78 and an area under the receiver operating characteristic curve (AUROC) of 0.84 on a DeepDRiD test split,

surpassing the previous best model evaluated on DeepDRiD (Tummala et al., 2023). Further, on a DrimDB test split, the accuracy and AUROC of our model were 1.0 and 1.0, respectively.

- Fovea and optic disc localization (Figure 1b). The center coordinates of the fovea and optic disc can be predicted using a multitask EfficientNet model. We trained the model on the combined ADAM, REFUGE and IDRID datasets which include images from eyes with age-related macular degeneration, glaucoma, diabetic retinopathy and healthy retinas (Fang et al., 2022; Orlando et al., 2020; Porwal et al., 2020). All datasets are publicly available. On our test split, the model achieved an average distance to the fovea and optic disc targets of 0.88 % of the image size. This corresponds to a mean distance of 3.08 pixels in the 350 x 350 pixel images used for training and testing.
- Vessel segmentation (Figure 1c). The segmentation method produces a mask of blood vessels in a fundus image using an ensemble of FR-UNets. The ensemble achieved an average Dice score of 0.887 on the test split of the FIVES dataset (Köhler et al., 2024). FIVES includes images with age-related macular degeneration, glaucoma, diabetic retinopathy and healthy retinas (Jin et al., 2022).
- Registration (Figure 1d). Two fundus images of the same eye can be aligned using SuperRetina (J. Liu et al., 2022). The deep learning based model detects key points on the vessel trees of the two images and matches them. This results in a registered version of the second image that is aligned with the first. SuperRetina produced registrations of at least acceptable quality in 98.5 % of the cases on the test split of the FIRE dataset (Hernandez-Matas et al., 2017).
- Circle cropping. The OpenCV-based implementation fastly crops the circular background from a fundus image. The circle is further resized to touch the edges of the image, which centers the fundus (Fu et al., 2019).

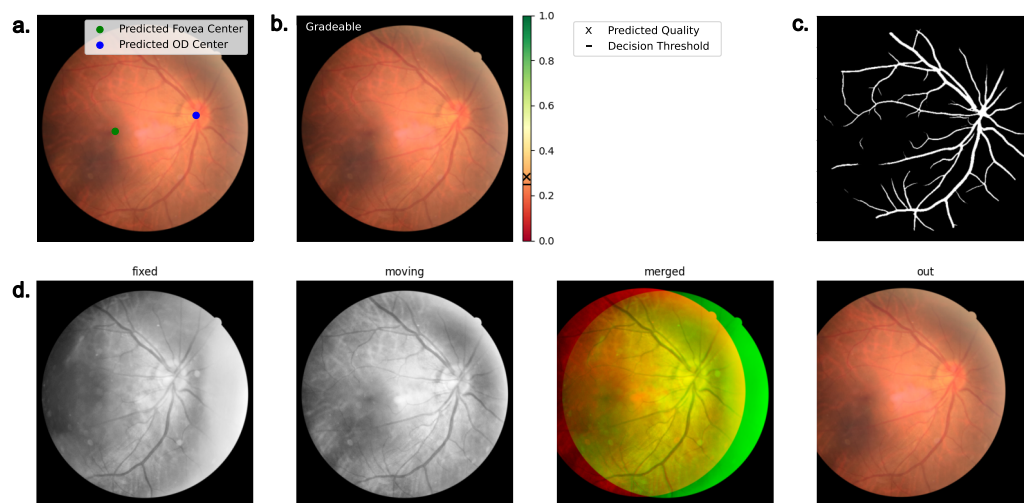


Figure 1: Examples for main functionalities of the Fundus Image Toolbox. (a.) Fovea and optic disc localization. (b.) Quality prediction. (c.) Vessel segmentation. (d.) Registration.

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Author contributions

Julius Gervelmeyer: Conceptualization, Software, Writing. Sarah Müller: Software. Ziwei Huang: Software: Code review & PyPI. Philipp Berens: Supervision, Writing: Review & Editing.

References

- Fang, H., Li, F., Fu, H., Sun, X., Cao, X., Lin, F., Son, J., Kim, S., Quellec, G., Matta, S., Shankaranarayana, S. M., Chen, Y.-T., Wang, C.-H., Shah, N. A., Lee, C.-Y., Hsu, C.-C., Xie, H., Lei, B., Baid, U., ... Xu, Y. (2022). ADAM challenge: Detecting age-related macular degeneration from fundus images. *IEEE Transactions on Medical Imaging*, 41(10), 2828–2847. <https://doi.org/10.1109/tmi.2022.3172773>
- Fu, H., Wang, B., Shen, J., Cui, S., Xu, Y., Liu, J., & Shao, L. (2019). Evaluation of retinal image quality assessment networks in different color-spaces. In *Medical image computing and computer assisted intervention – MICCAI 2019* (pp. 48–56). Springer International Publishing. https://doi.org/10.1007/978-3-030-32239-7_6
- Hernandez-Matas, C., Zabulis, X., Triantafyllou, A., Anyfanti, P., Douma, S., & Argyros, A. A. (2017). FIRE: Fundus image registration dataset. *Modeling and Artificial Intelligence in Ophthalmology*, 1(4), 16–28. <https://doi.org/10.35119/maio.v1i4.42>
- Jin, K., Huang, X., Zhou, J., Li, Y., Yan, Y., Sun, Y., Zhang, Q., Wang, Y., & Ye, J. (2022). Fives: A fundus image dataset for artificial intelligence based vessel segmentation. *Scientific Data*, 9(1), 475. <https://doi.org/10.1038/s41597-022-01564-3>
- Köhler, P., Fadugba, J., Berens, P., & Koch, L. M. (2024). Efficiently correcting patch-based segmentation errors to control image-level performance. *Accepted at Medical Imaging with Deep Learning*. <https://openreview.net/forum?id=DDHRGHfwji>
- Liu, J., Li, X., Wei, Q., Xu, J., & Ding, D. (2022). Semi-supervised keypoint detector and descriptor for retinal image matching. *Computer Vision – ECCV 2022*, 593–609. https://doi.org/10.1007/978-3-031-19803-8_35
- Liu, R., Wang, X., Wu, Q., Dai, L., Fang, X., Yan, T., Son, J., Tang, S., Li, J., Gao, Z., Galdran, A., Poorneshwaran, J. M., Liu, H., Wang, J., Chen, Y., Porwal, P., Wei Tan, G. S., Yang, X., Dai, C., ... Zhang, P. (2022). DeepDRiD: Diabetic retinopathy—grading and image quality estimation challenge. *Patterns*, 3(6), 100512. <https://doi.org/10.1016/j.patter.2022.100512>
- Orlando, J. I., Fu, H., Barbosa Breda, J., Keer, K. van, Bathula, D. R., Diaz-Pinto, A., Fang, R., Heng, P.-A., Kim, J., Lee, J., Lee, J., Li, X., Liu, P., Lu, S., Murugesan, B., Naranjo, V., Phaye, S. S. R., Shankaranarayana, S. M., Sikka, A., ... Bogunović, H. (2020). REFUGE challenge: A unified framework for evaluating automated methods for glaucoma assessment from fundus photographs. *Medical Image Analysis*, 59, 101570. <https://doi.org/10.1016/j.media.2019.101570>
- Porwal, P., Pachade, S., Kokare, M., Deshmukh, G., Son, J., Bae, W., Liu, L., Wang, J., Liu, X., Gao, L., Wu, T., Xiao, J., Wang, F., Yin, B., Wang, Y., Danala, G., He, L., Choi, Y. H., Lee, Y. C., ... Mériaudeau, F. (2020). IDRiD: Diabetic retinopathy – segmentation and grading challenge. *Medical Image Analysis*, 59, 101561. <https://doi.org/10.1016/j.media.2019.101561>
- Sevik, U., Kose, C., Berber, T., & Erdol, H. (2014). Identification of suitable fundus images using automated quality assessment methods. *Journal of Biomedical Optics*, 19(4), 046006. <https://doi.org/10.1117/1.JBO.19.4.046006>
- Tummala, S., Thadikemalla, V. S. G., Kadry, S., Sharaf, M., & Rauf, H. T. (2023). Efficient-

NetV2 based ensemble model for quality estimation of diabetic retinopathy images from DeepDRiD. *Diagnostics*, 13(4), 622. <https://doi.org/10.3390/diagnostics13040622>

Zhou, Y., Wagner, S. K., Chia, M. A., Zhao, A., Xu, M., Struyven, R., Alexander, D. C., Keane, P. A., & others. (2022). AutoMorph: Automated retinal vascular morphology quantification via a deep learning pipeline. *Translational Vision Science & Technology*, 11(7), 12–12. <https://doi.org/10.1167/tvst.11.7.12>