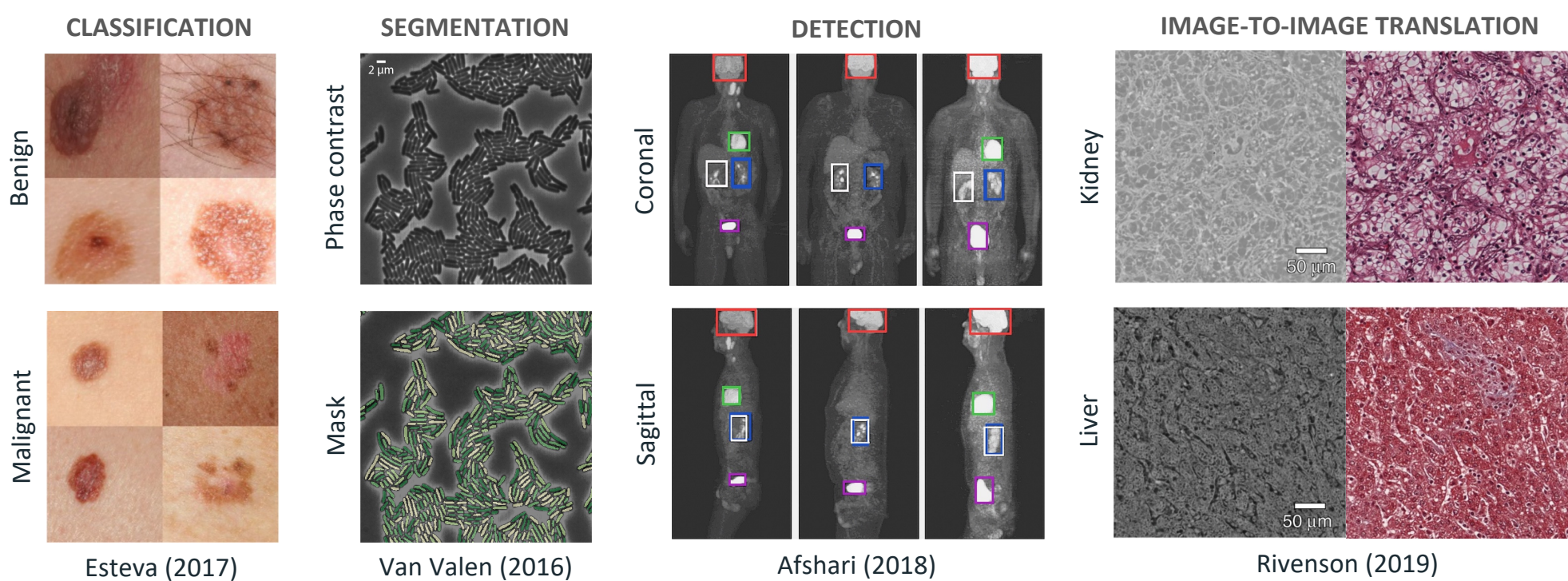


Abstract

Deep learning has transformed many aspects of industrial pipelines recently. Scientists involved in biomedical imaging research are also benefiting from the power of AI to tackle complex challenges (Kim, 2019). Although academic community has widely accepted image processing tools, such as scikit-image, ImageJ, there is still a need for a tool which integrates deep learning into biomedical image analysis. We propose a minimal, but convenient Python package based on PyTorch with common deep learning models, extended by flexible trainers and medical datasets. In this work, we also share theoretical dive in the form of course as well as minimal tutorials to run Android applications, containing models trained with Farabio.



Package Structure

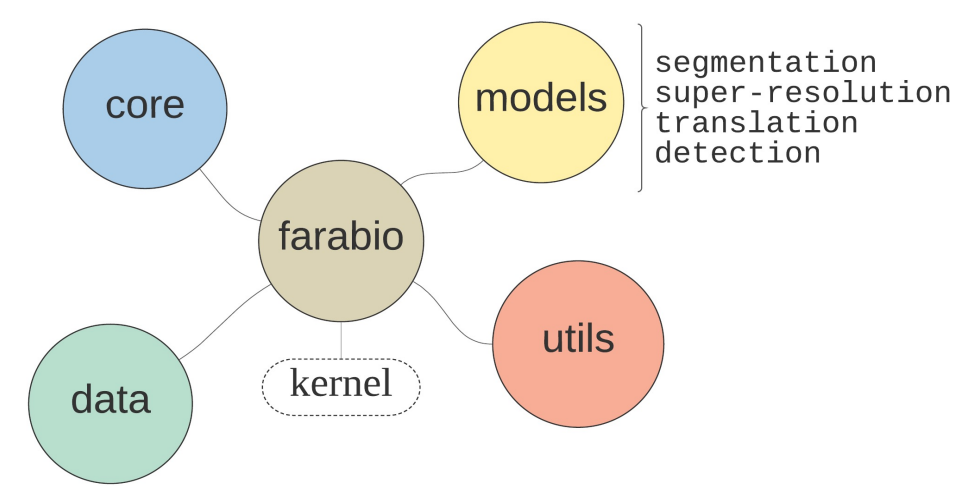


Fig 1. Package structure diagram

farabio package has 4 modules:

- **.core**: base trainer classes
- **.data**: preprocessing, datasets
- **.models**: architectures, trainers
- **.utils**: log, visualization, helpers

Every deep learning model trainer derives from the **core** module. Based on the type, it has either **ConvnetTrainer** or **GanTrainer** as its parent.

farabio incorporates and modifies common deep learning models from open-source code released on GitHub (see the docs)

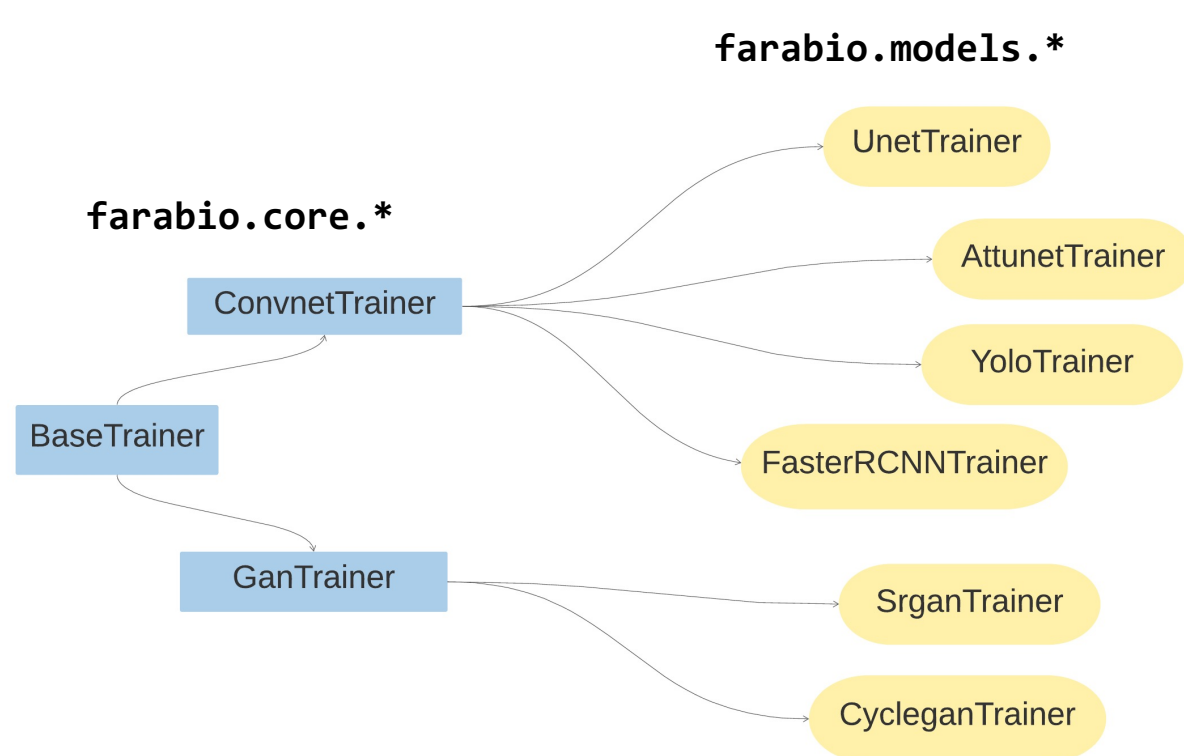
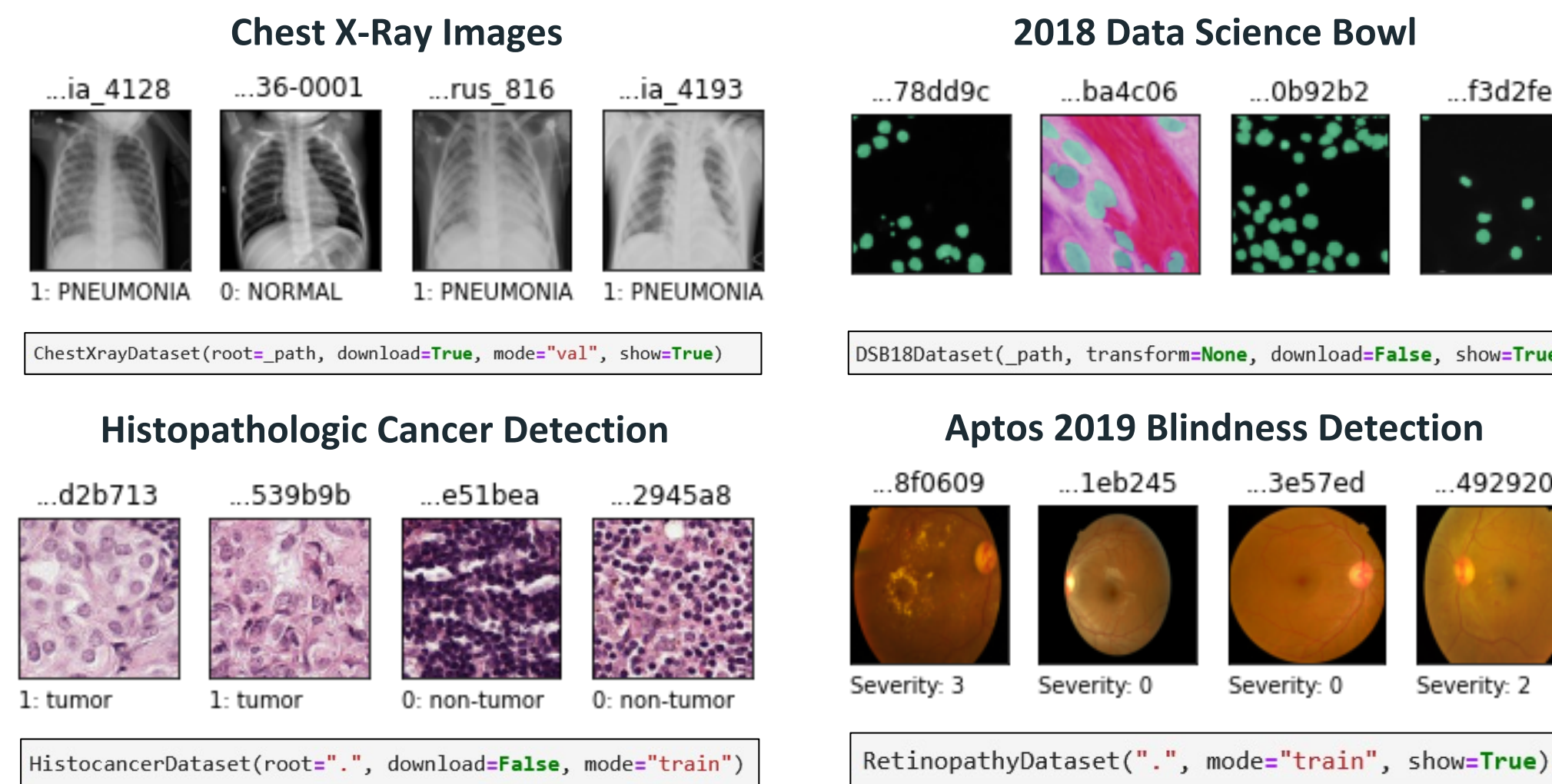


Fig 2. Inheritance diagram of trainers

Biomedical Datasets

Several publicly available biomedical datasets which are retrieved from ISBI, MICCAI and Kaggle can be loaded from `farabio.data.biodatsets` module:



Lifecycle of Trainers

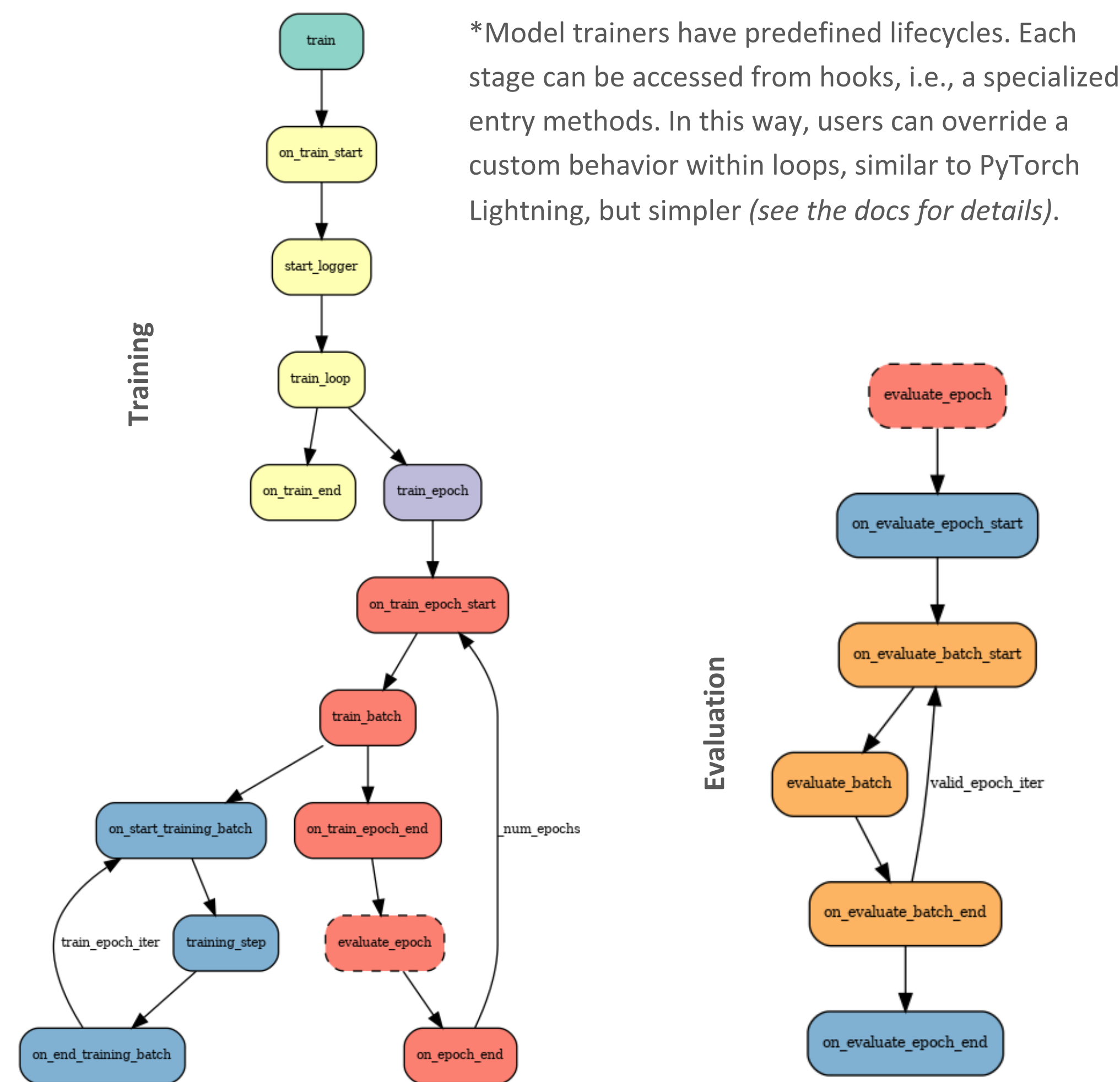
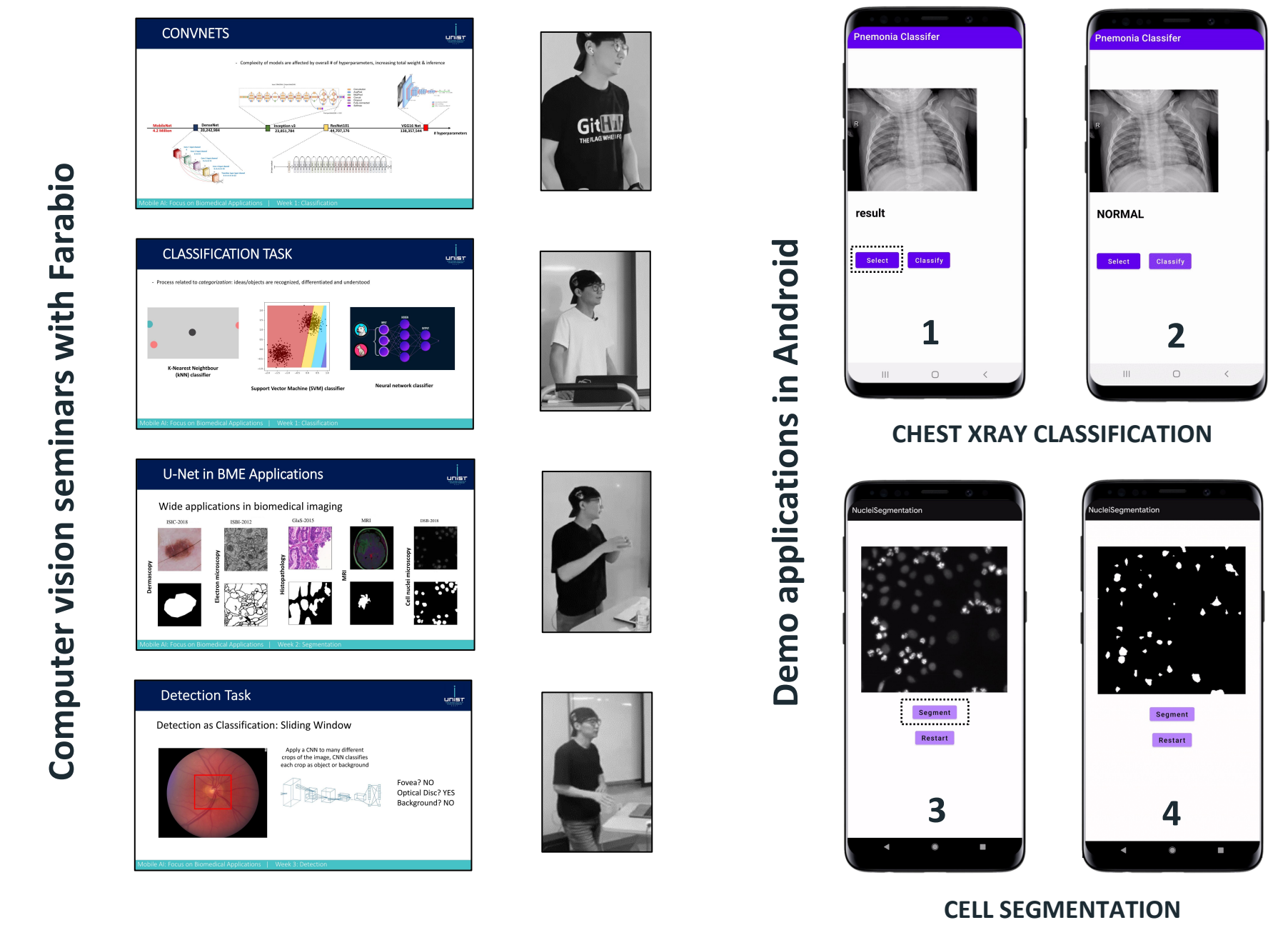


Fig 3. Diagrams of ConvnetTrainer lifecycle in training and evaluation loops

Mobile AI: Focus on biomedical applications

Farabio package was used to support computer vision seminars for biomedical engineers. It also integrates mobile-friendly models to deploy on mobile devices.



Future Works

In perspective, the vision of farabio package is to become an important player of PyTorch ecosystem, with research and academic community of biomedical engineering adopting it widely for different deep learning purposes. This is only possible with robust architectural foundations, rich dataset extensions and openness to new ideas, collaborations, which we aspire to cultivate.

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Links

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