Our Offer

CuraMate AI Development makes model development for segmentation or detection tasks significantly more efficient and therefore faster and less costly. If you are interested in robust, custom imaging AI models, we are the right partner for you. We are open to developing these for you, together with you, or to supply you with our optimized tooling.

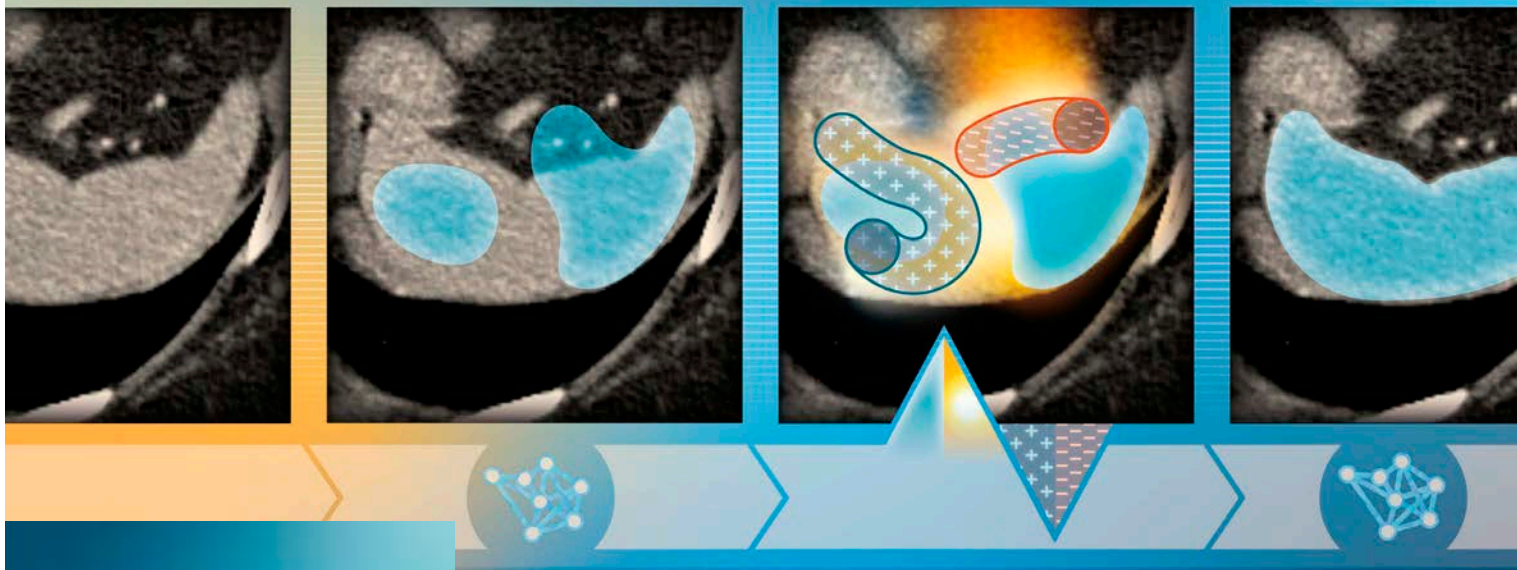
For a personal demonstration, technical or licensing questions and other inquiries, please contact our experts.We offer customized solutions and seamless integration tailored to partner-specific needs.

Fraunhofer MEVIS is an applied research institute developing software under an ISO-certified quality management system. Using our efficient toolkits, we rapidly develop clinical application prototypes, and also supply algorithms or larger software components for integration into medical products.

Visit our CuraMate Website

Fraunhofer MEVIS

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AI Development

CURA MATE

Accelerate AI Development with Active Learning

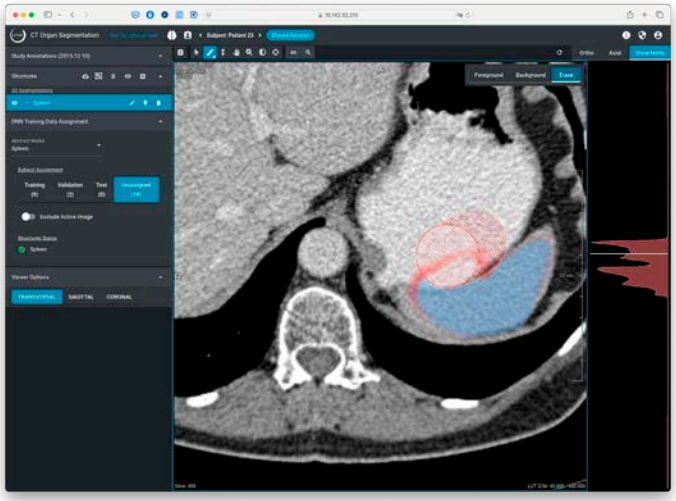
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Solution

CuraMate AI Development implements the iterative process ("training loop") of using the best currently available model to pre-segment a case, enabling experts to correct any AI-made errors, and then triggering the next training step to produce an improved model for the following round.

- **Integrated Toolkit**
  Our web-based data curation frontend is tightly integrated with model training and inference components in the backend. Each trained AI model is run on the whole dataset so that annotators can see the results of the most recent model, perform corrections, and trigger the next training iteration.

- **Uncertainty-Driven Training Loop**
  The uncertainty guidance allows you to focus labeling effort on difficult or unusual cases to avoid models that perform well on average but fail spectacularly more often than necessary. This is particularly useful with large datasets, because experts do not have to spend time on cases on which the segmentation already works well.



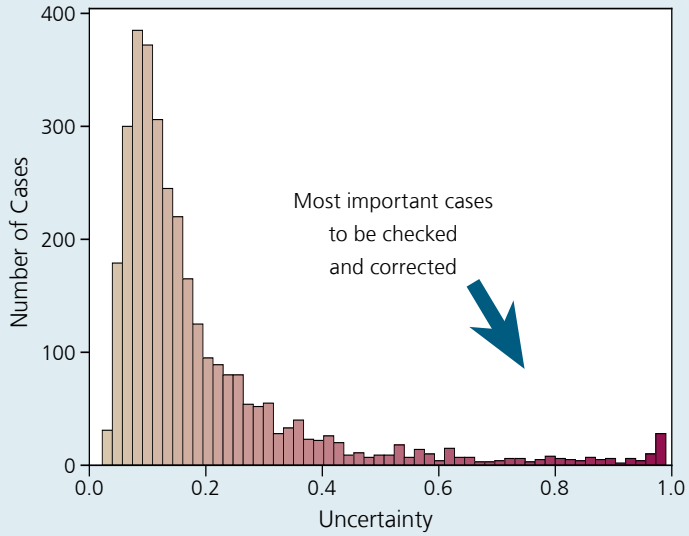


Fig. 1: A model trained on 100 cases shows high uncertainty only on a fraction of the 3200 MRIs under consideration.

Benefits

Robust, fully automatic segmentation algorithms play an important role in modern medical image analysis. Although there is a wide variety of algorithms on the market already, the need for improved diagnostics and interventional support requires further developments.

CuraMate AI Development increases efficiency in the model development process and reduces the necessary human effort. In an example study on liver segmentation, we have shown that it is possible to spend nearly ninety percent less time on annotation and obtain a model as robust as when training with the complete data pool [1].

[1] G. Chlebus et al.: Robust Segmentation Models Using an Uncertainty Slice Sampling-Based Annotation Workflow.
IEEE Access. 2022; Vol. 10. doi:10/hsjd

[2] R. Schäfer et al.: Overcoming data scarcity in biomedical imaging with a foundational multi-task model.
Nature Computational Sciences. 2024; Vol. 4(7). doi:10/m9b5

Key Features

Our uncertainty-driven training loop helps to reduce the necessary labeling effort and therefore development costs in multiple ways:

Training with Local Corrections

Our model training can incorporate local corrections on any number of slices and does not require each case to be fully labeled.

Uncertainty Guidance

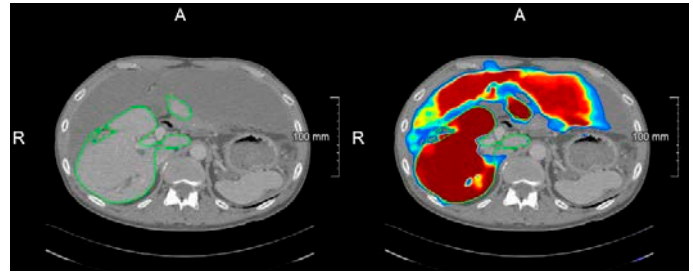
Each segmentation model trained during the iterative development process estimates its uncertainty. This is used to guide users to cases, slices, and areas that would benefit from additional labels. Such guidance is particularly useful and time-saving on large datasets (Fig. 1).

Efficient, Guided Reading Workflow

The data curation workflow is customized to project-specific needs and processes for maximal efficiency.

Foundation Model Support

The training time for the next model iteration can be reduced to a few seconds through the use of our award-winning foundation model [2], training only a small adapter.



Preliminary liver segmentation in patient with ascites; uncertainty arises in areas where the model normally expects liver tissue.