Label-Label-Efficient Machine Learning Algorithms for the Clinical Diagnostics of Urinary Tract Infections

CASUS
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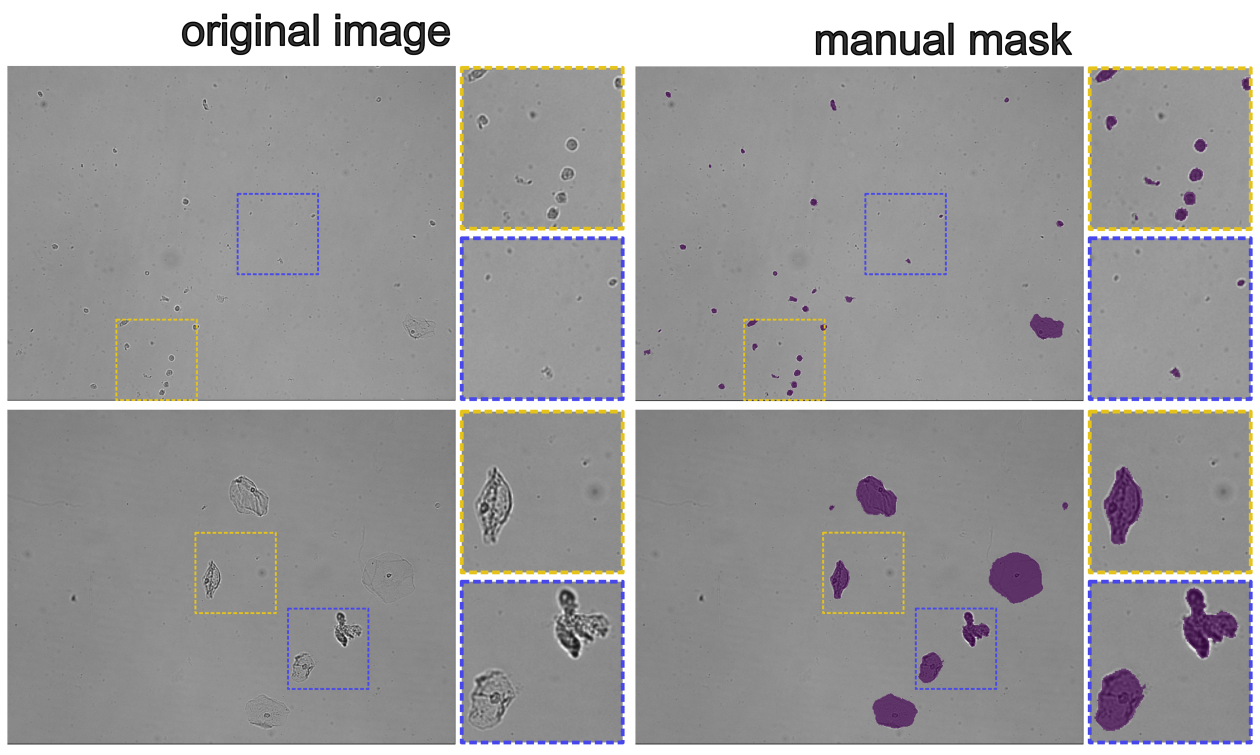
Abstract

Advancements in machine learning carry the potential to revolutionize clinical diagnostics, but their effective application often demands extensive datasets meticulously annotated by specialized biomedical experts — a time-consuming and laborious task.

In our research, we strive to overcome this challenge, by exploring diverse techniques leveraging unlabeled or weakly labeled data, which is comparatively easier to obtain. Our focus lies specifically in the domain of biomedical image analysis, particularly in the binary segmentation of urine microscopy images — a crucial first step in automating the detection of urinary tract infections.



Ilastik

Ilastik (Sommer, Christoph et al., 2011) is an open-source software that excels in semantic segmentation using the following approach:

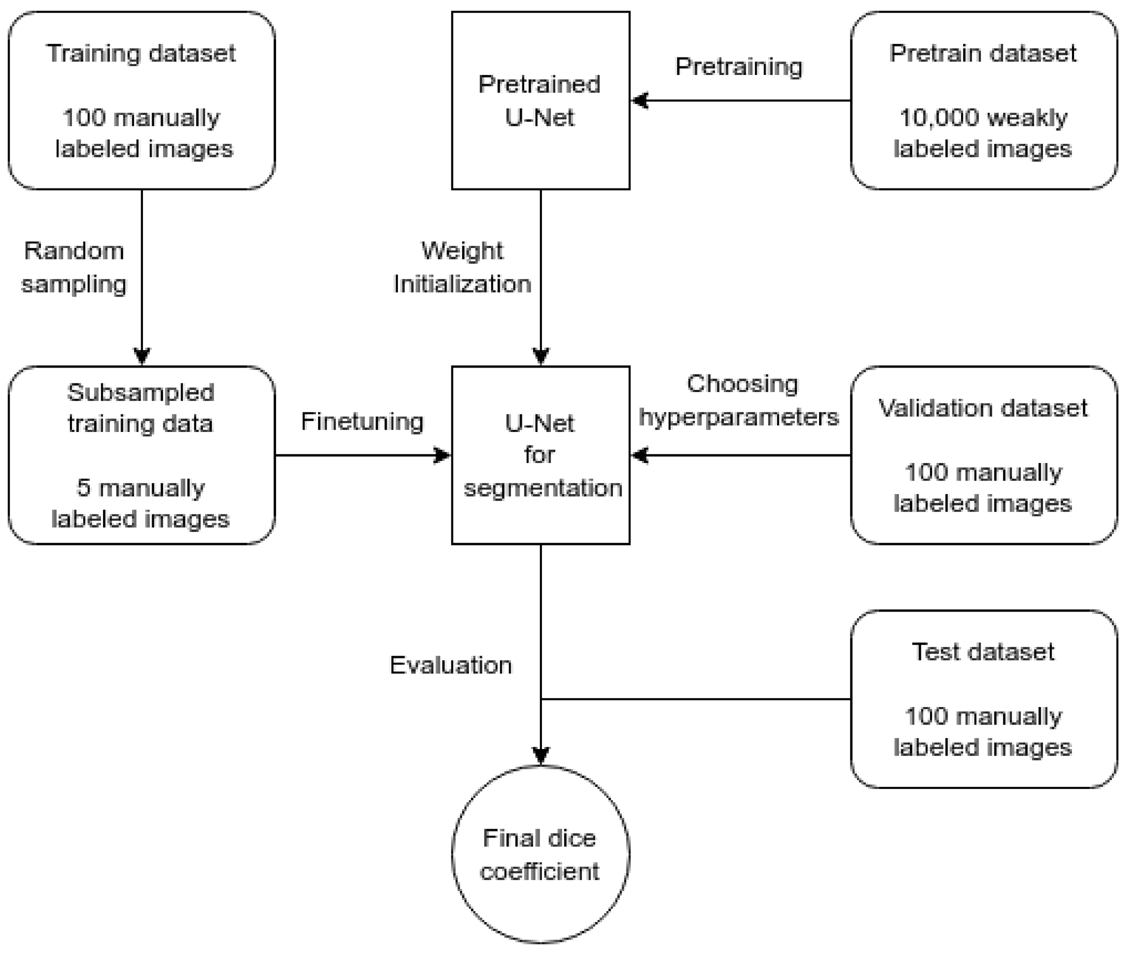
- Extract features like color, edge or texture using simple heuristics
- Categorize pixels by using random forest classifier on extracted features
- Utilize active learning to refine predictions based on user feedback

Ilastik masks we obtained achieved about 60% dice coefficeint.

Our Methodology

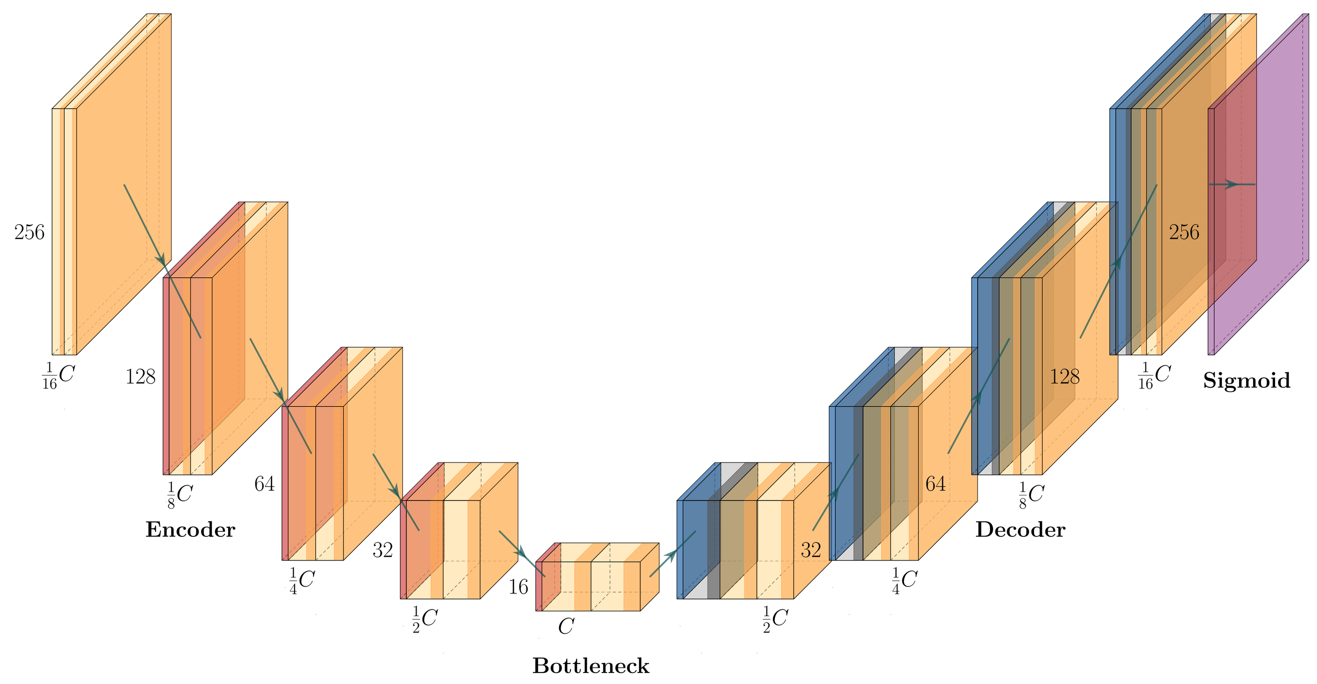
The images in our training set were enough to reasonably train a fully supervised binary segmenation model. Our goal was to see if we can reduce the amount of data used while maintaining good performance. We decided on the following approach:

- Use pretrain dataset with no manual labels to obtain pretrained model
- Finetune using random subset of 5 images from the training dataset
- Use the whole validation and test datasets to maintain credibility



The architecture

We opted for the U-Net (Ronneberger et al., 2015) architecture, a gold standard in microscopy computer vision. Additionally, we explored diverse pretraining techniques: two weak labeling approaches, two pretext tasks, and an autoencoder.

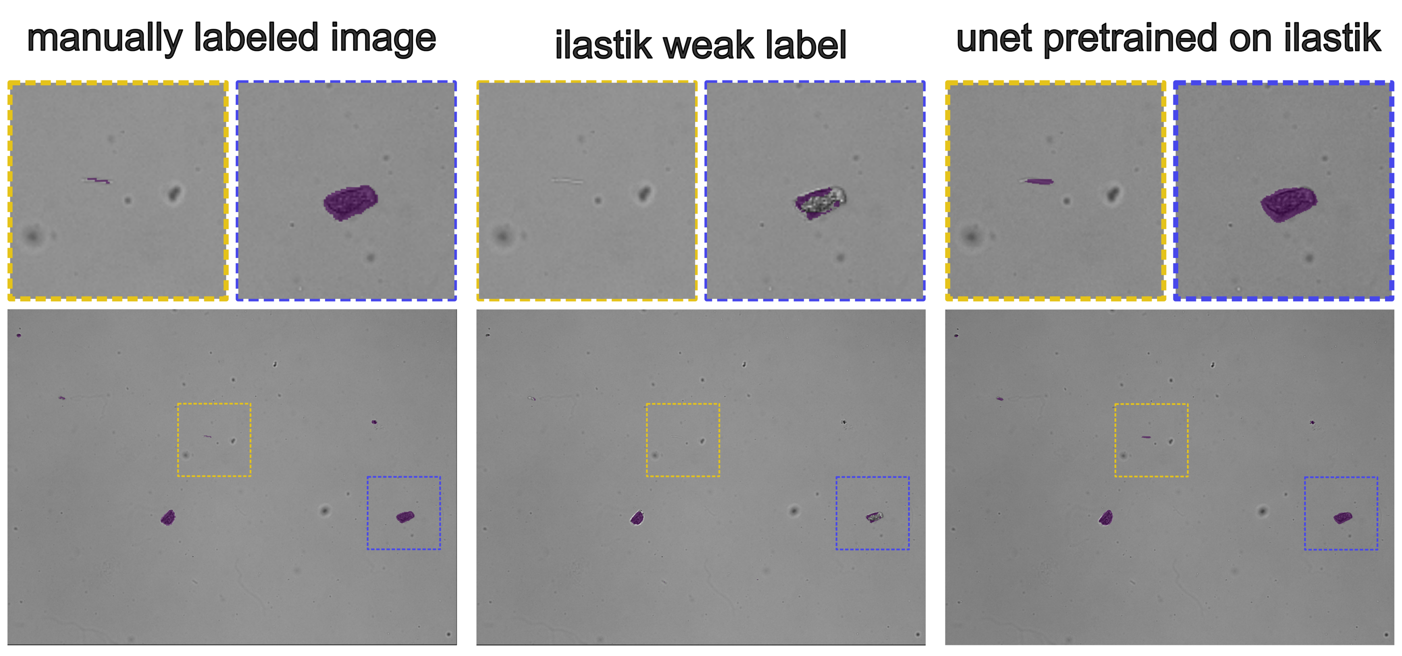


Approach	Experiment #1	Experiment #2	Experiment #3	Experiment #4	Experiment #5	Mean ± std
Training from scratch	0.014	0.601	0.689	0.696	0.690	0.538 ± 0.264
Thresholding (Weak Labels)	0.680	0.716	0.747	0.663	0.734	0.708 ± 0.032
Ilastik (Weak Labels)	**0.791**	**0.793**	**0.796**	**0.783**	**0.800**	**0.792 ± 0.006**
Region Duplication (Pretext Task)	0.737	0.690	0.691	0.671	0.691	0.696 ± 0.022
Standard Deviation (Pretext Task)	0.707	0.766	0.751	0.695	0.737	0.731 ± 0.026
Autoencoder	0.751	0.750	0.671	0.670	0.715	0.712 ± 0.036

Conclusion

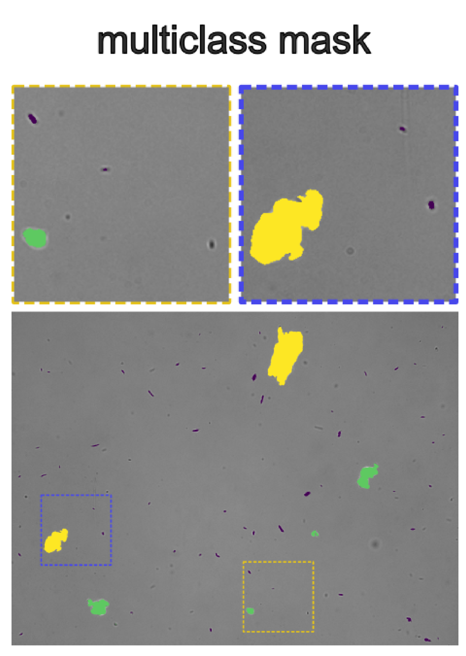
All in all, when the training dataset is extremely sparse, pretraining usually helps with accuracy and the convergence.

While most methods only offered a small improvement, using ilastik weak labels offered much better results.



Future Work

- Evaluate the quality of latent representations
- Try move advanced autoencoder architectures
- Move on to multiclass segmentation



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