MA Final

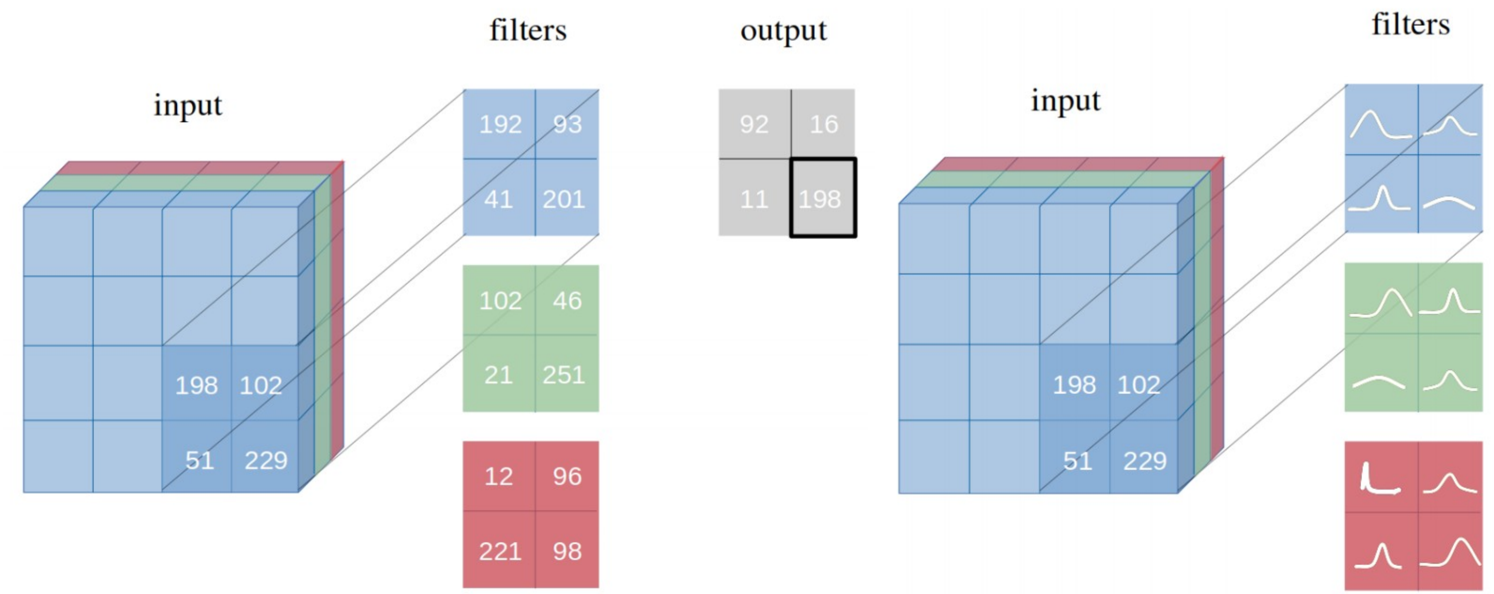
Bayesian Deep Learning for Medical Image Segmentation

Presenter:
Jyotirmay Senapati

Advisor:
Abhijit Guha Roy
Dr. Sebastian Pölsterl
Prof. Dr. Christian Wachinger

What is Bayesian Deep Learning?

- Network with probability distributions over weights.
- Enables uncertainty / confidence estimations.



Shridhar, K., Laumann, F. and Liwicki, M., 2018. Uncertainty Estimations by Softplus normalization in B
Convolutional Neural Networks with Variational Inference. *arXiv preprint arXiv:1806.05978*.

Approximate Variational Inference

- Issues with Traditional Bayesian Neural Networks.
  - Scalability.
  - Difficulty in training.
  - More data hungry, often unstable.

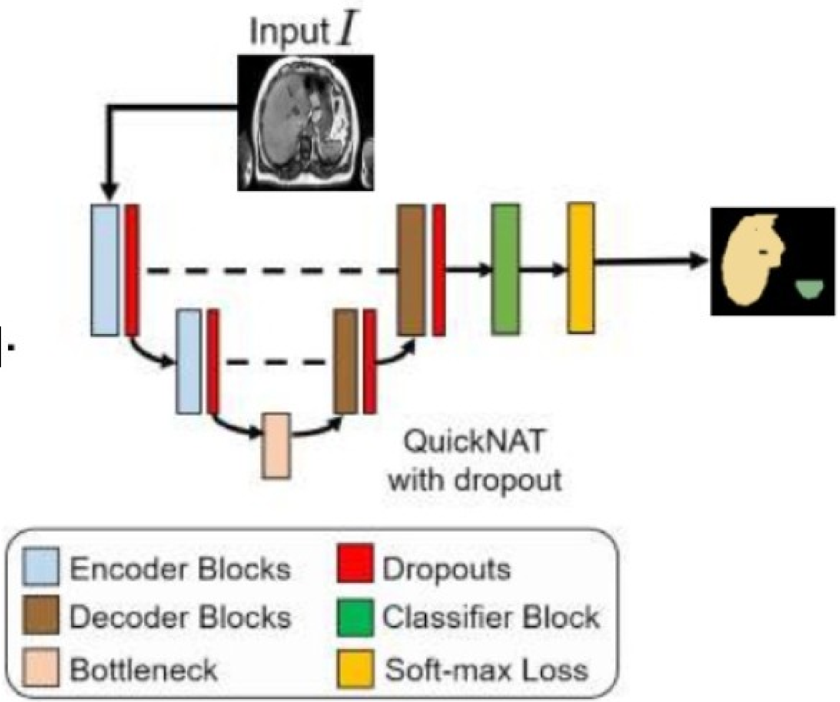
- Approximate Variational Inference on Deep Networks
  - Variational Monte-Carlo Dropouts.
  - Probabilistic U-Net using Variational autoencoder.
  - Hierarchical Probabilistic U-Net.
  - The ` Re-Parameterization ` trick on DNNs.

Medical Image Data and Segmentation

- Modality: Dixon Sequence MRI
- Datasets:
  - KORA (xx scans)
  - UK Bio-Bank (yy scans)
  - NAKO (zz scans)
- Target organs: Liver, Spleen.
- Aim: Analyze Diabetes and Visualization, more details later …

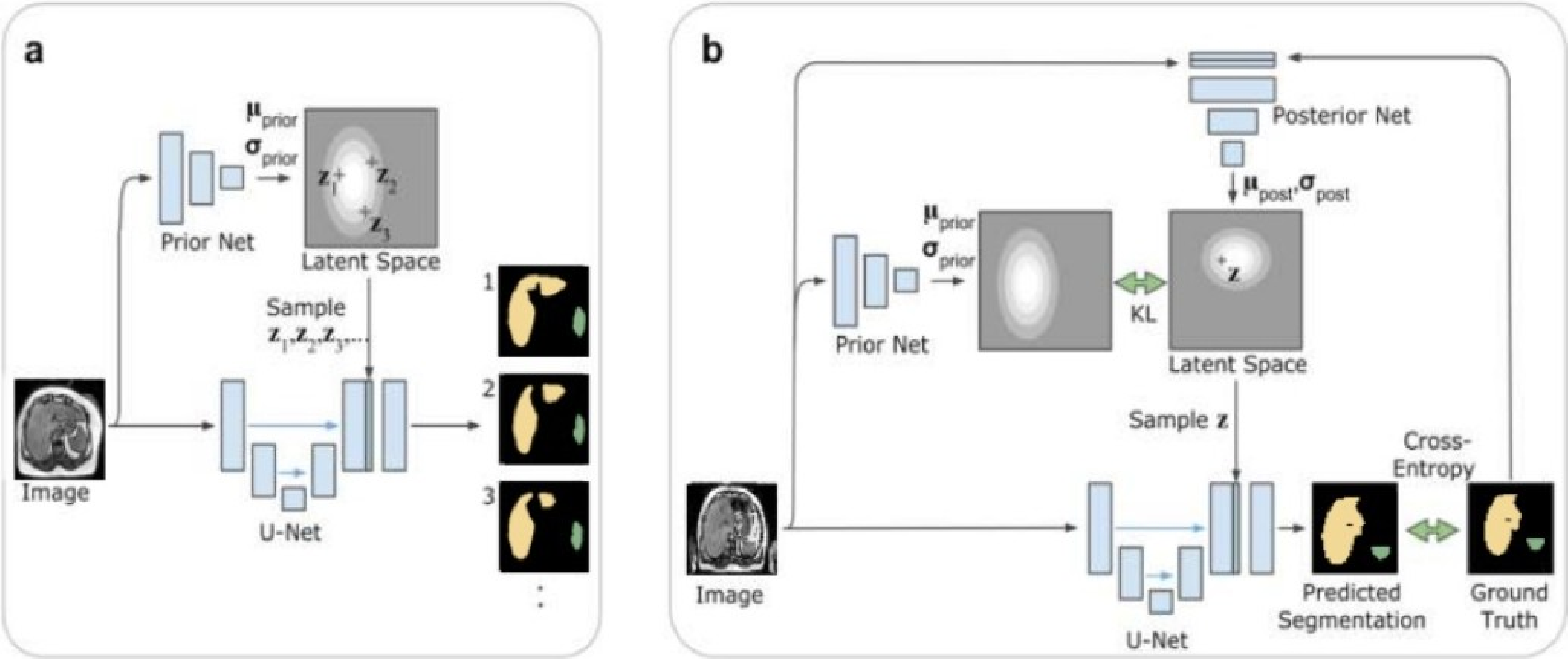
Variational Monte Carlo Dropout

- Addition of dropout lay
- Dropouts during infere



Roy, A.G., Conjeti, S., Navab, N., Wachinger, C. and Alzheimer's Disease Neuroimaging Initiative, 201
Bayesian QuickNAT: Model uncertainty in deep whole-brain segmentation for structure-wise quality c
NeuroImage, *195*, pp.11-22.

Probabilistic U-Net

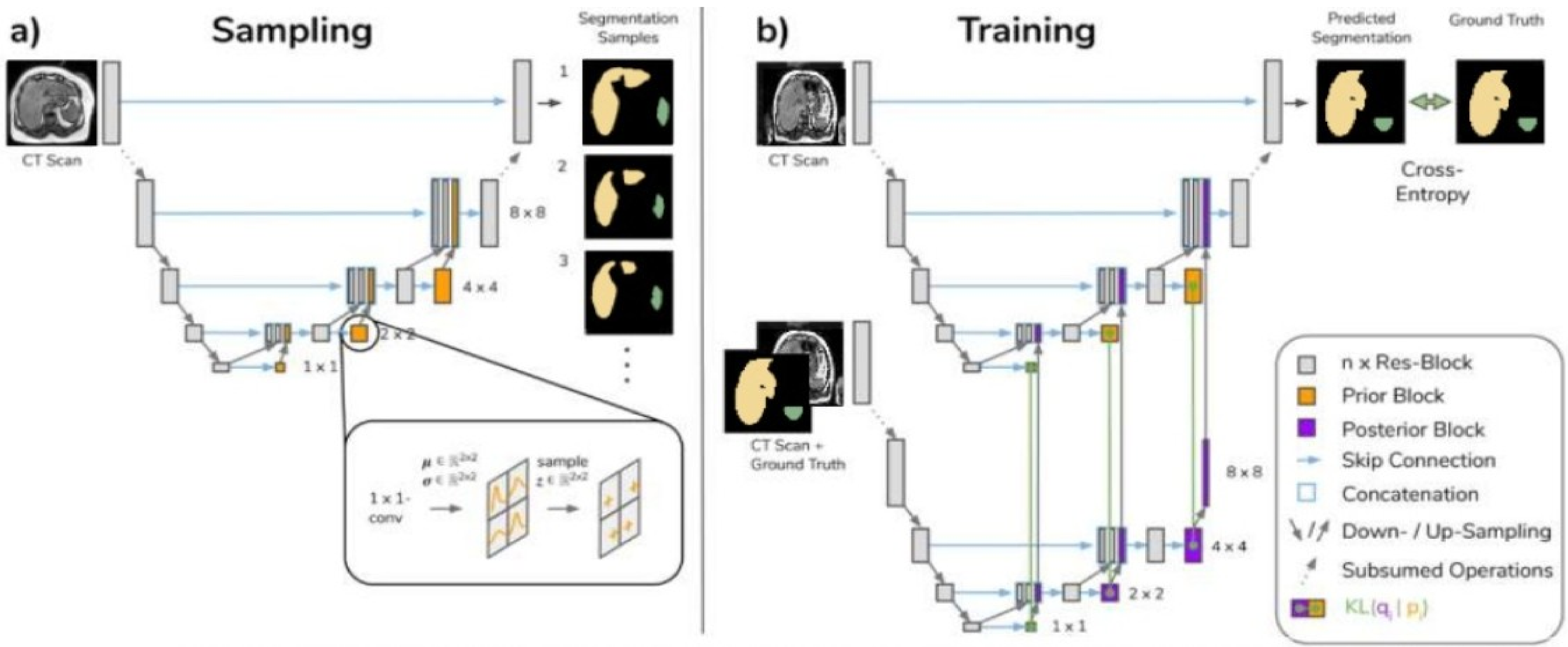


- Learning latent of segmentation maps during training.
- Aids in generating all plausible segmentations while testing.

Kohl, S., Romera-Paredes, B., Meyer, C., De Fauw, J., Ledsam, J.R., Maier-Hein, K., Eslami, S.A., Rezend and Ronneberger, O., 2018. A probabilistic u-net for segmentation of ambiguous images. In *Advances Information Processing Systems* (pp. 6965-6975).

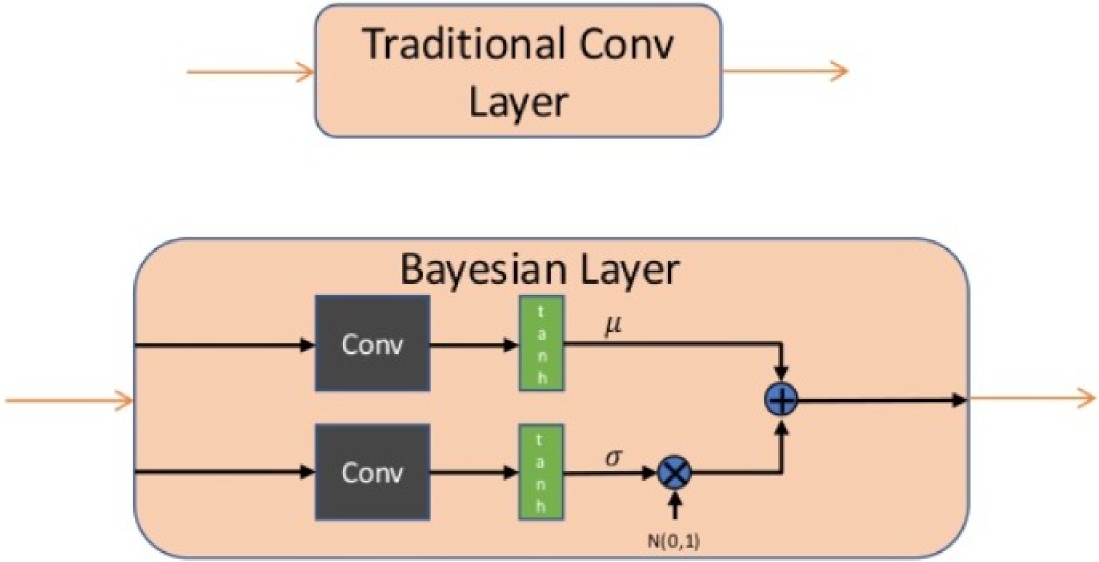
Hierarchical Probabilistic U-Net

- Build with the idea of extended probabilistic U-Net.



Kohl, S.A., Romera-Paredes, B., Maier-Hein, K.H., Rezende, D.J., Eslami, S.M., Kohli, P., Zisserman, A. a Ronneberger, O., 2019. A Hierarchical Probabilistic U-Net for Modeling Multi-Scale Ambiguities. *arXiv preprint arXiv:1905.13077*.

Bayesian F-CNN using Re-parameterization



Reparameterization Trick: $g_\theta(\varepsilon) = \mu_\theta + \varepsilon\sigma_\theta$

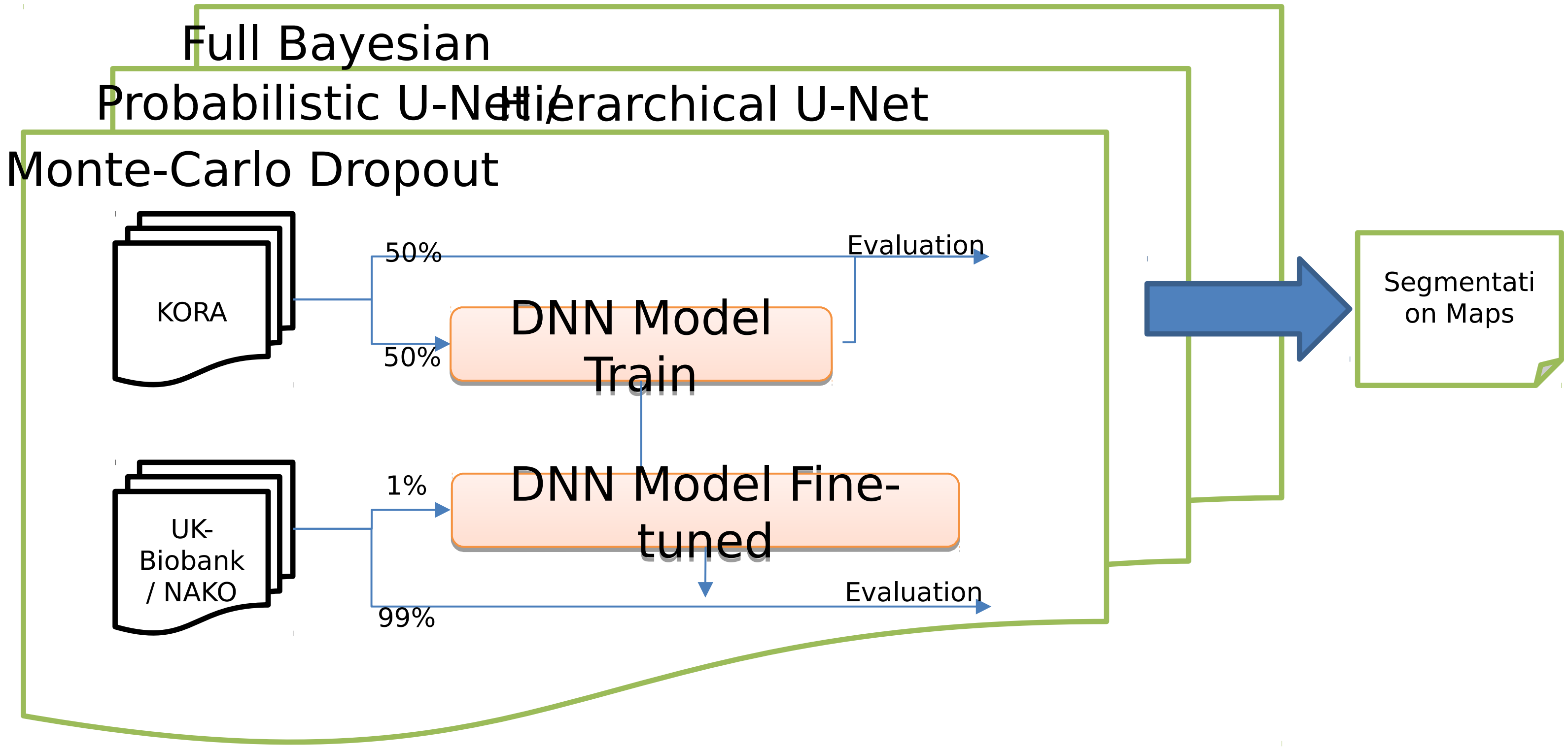
$\varepsilon \sim \mathcal{N}(0,1)$

Kingma, D.P., Salimans, T. and Welling, M., 2015. Variational dropout and the local reparameterizatio
In *Advances in Neural Information Processing Systems* (pp. 2575-2583).

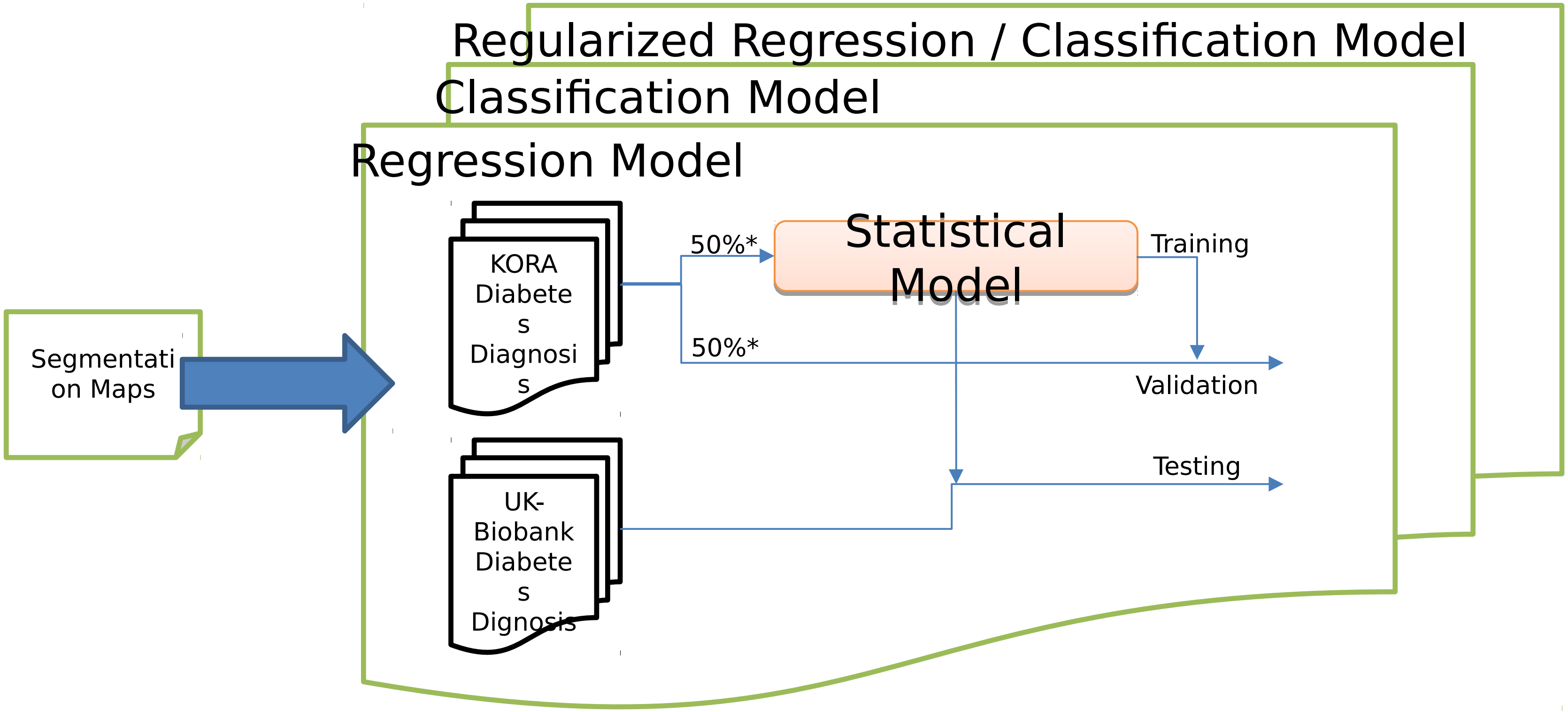
The Overall Task

- Stage 1: Liver and Spleen segmentation of whole-body Dixon MRI scans with their corresponding Uncertainty.
- Stage 2: Integrate and optimize the web app for whole-body segmentation visualization.
- Stage 3: Identify its impact for early onset Diabetes.

Training Strategy Part I



Training Strategy Part II



*Total Dataset = X diabetic volumes + Y non-diabetic volumes
Train-set = Test-set = X/2 + Y/2

Stage 1: Segmentation Challenge

Multi-dataset setting (KORA, NAKO, UK Biobank) with annotations only in KORA dataset.

- Resolution is different across dataset.
- Orientation are not standardized.
- Difference in final size and contrast.

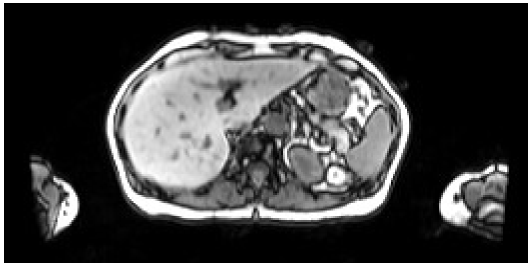
Stage 1: Segmentation Challenge

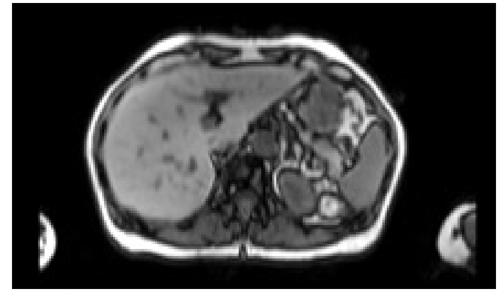
- Standardized pre-processing pipeline helps.
  - Reorientation to a standard orientation.
  - Down-sampling to a standard orientation.
- Acceptable performance achieved across dataset.
- Results are not yet perfect, hence uncertainty plays a big role.

Stage 1: processed Outputs

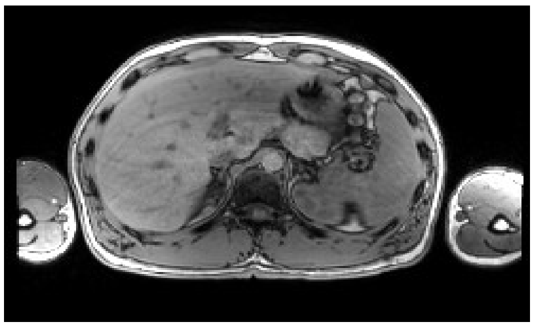
Original | **Processed**

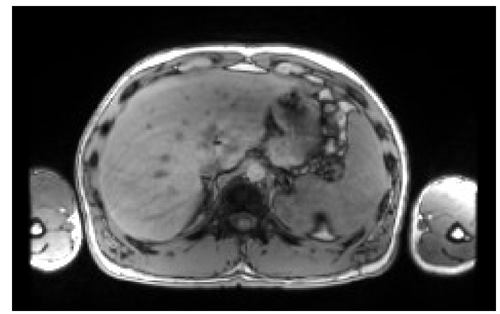
KORA



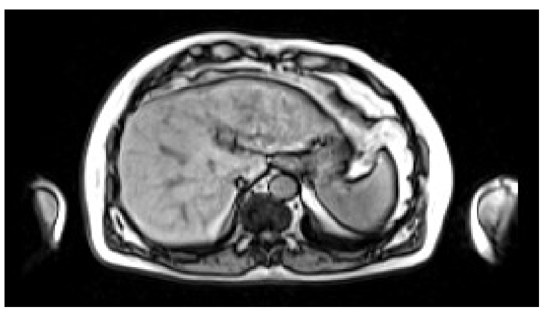


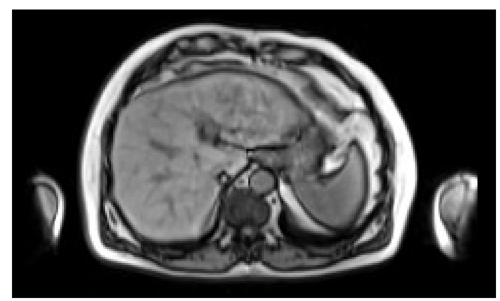
NAKO





UK-BioBank





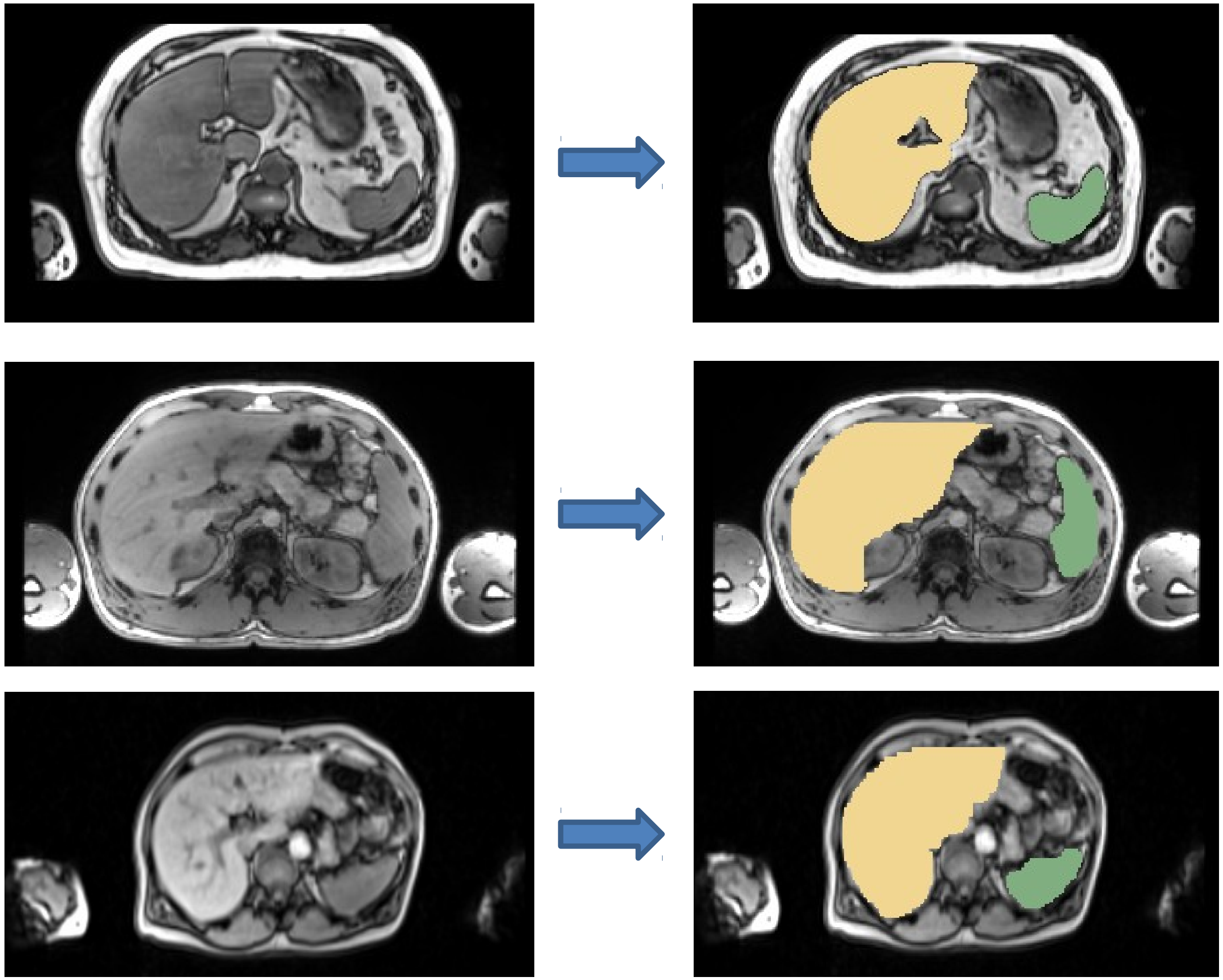
Stage 1: Segmentation Outputs

Processed **Segmentation**

KORA

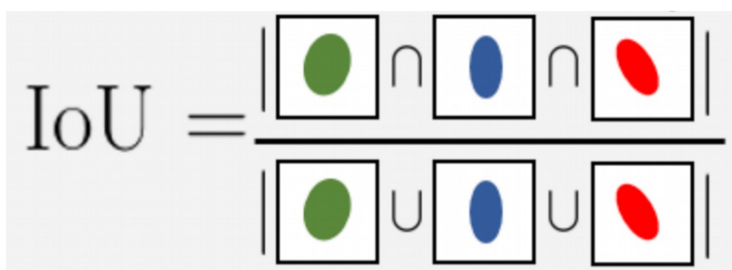
NAKO

UK-BioBank



Stage 1: Uncertainty

- Intersection over Union(IoU).
- Hausdorff Surface Distance.
- Normalized cross correlation.
- Generalised Energy Distance.
- Why IoU?
  - Independent of ground truth.
  - Alleviate labelled data scarcity.



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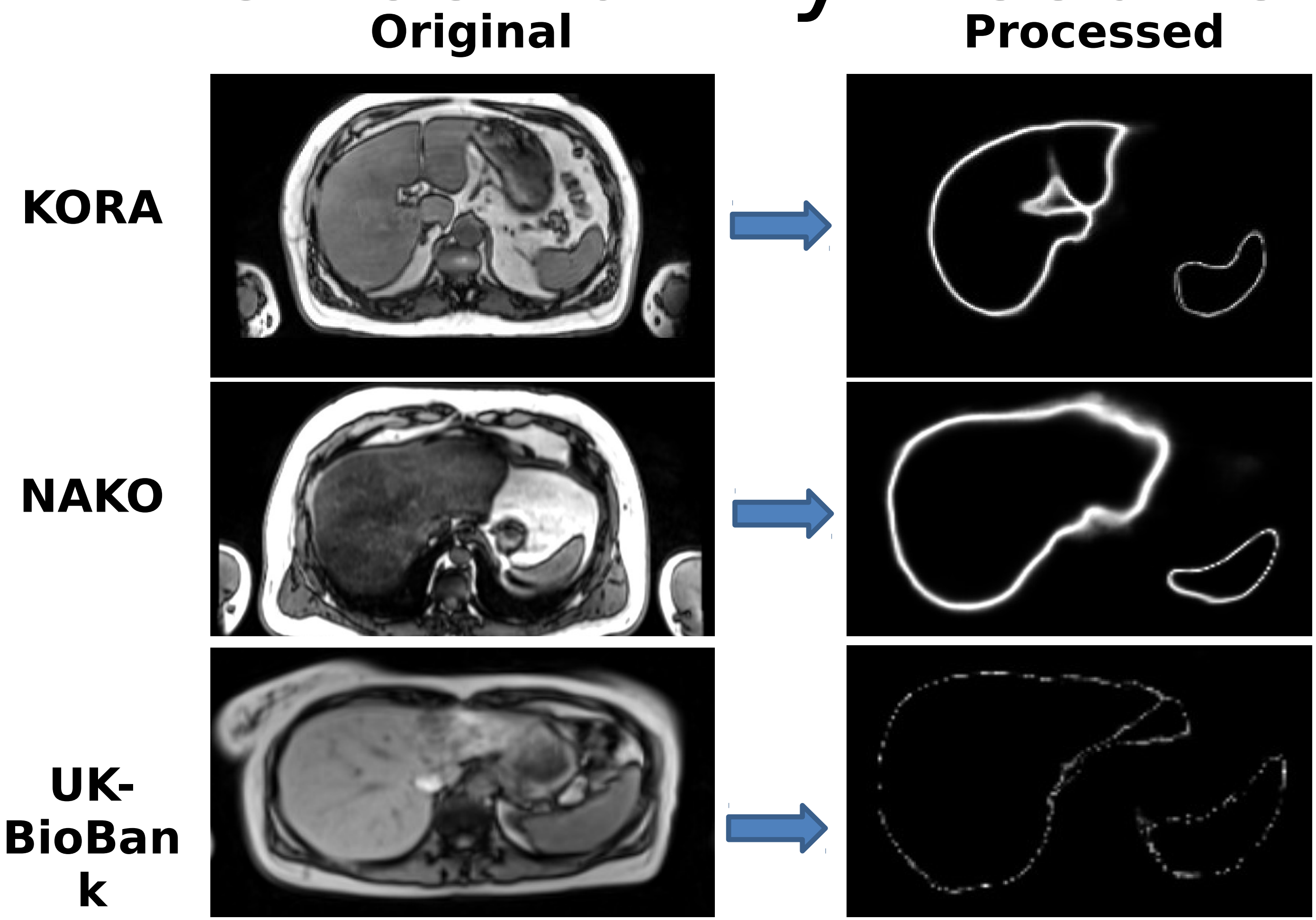
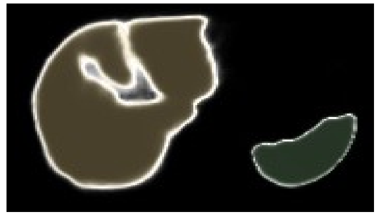
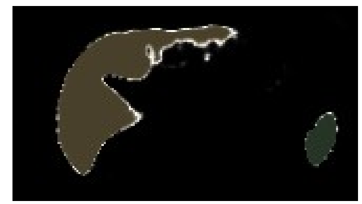
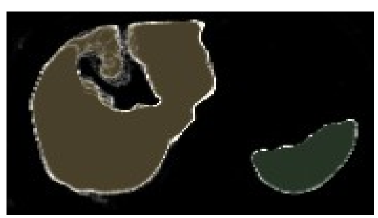
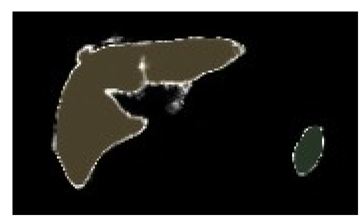
Stage 1: Segmentation and Uncertainty Results

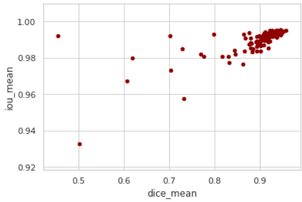
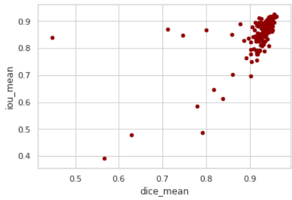
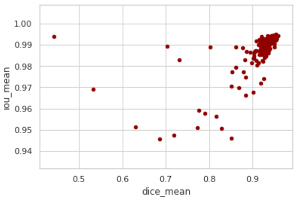
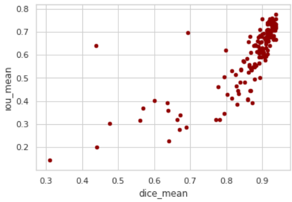


Stage 1: More outputs

Models	**KORA(2461885)**	**UK-Biobank(5452558)**
MC Dropout		
Probabilistic U-Net		
Hierarchical U-Net		
Full Bayesian		

Stage 1: Other Findings

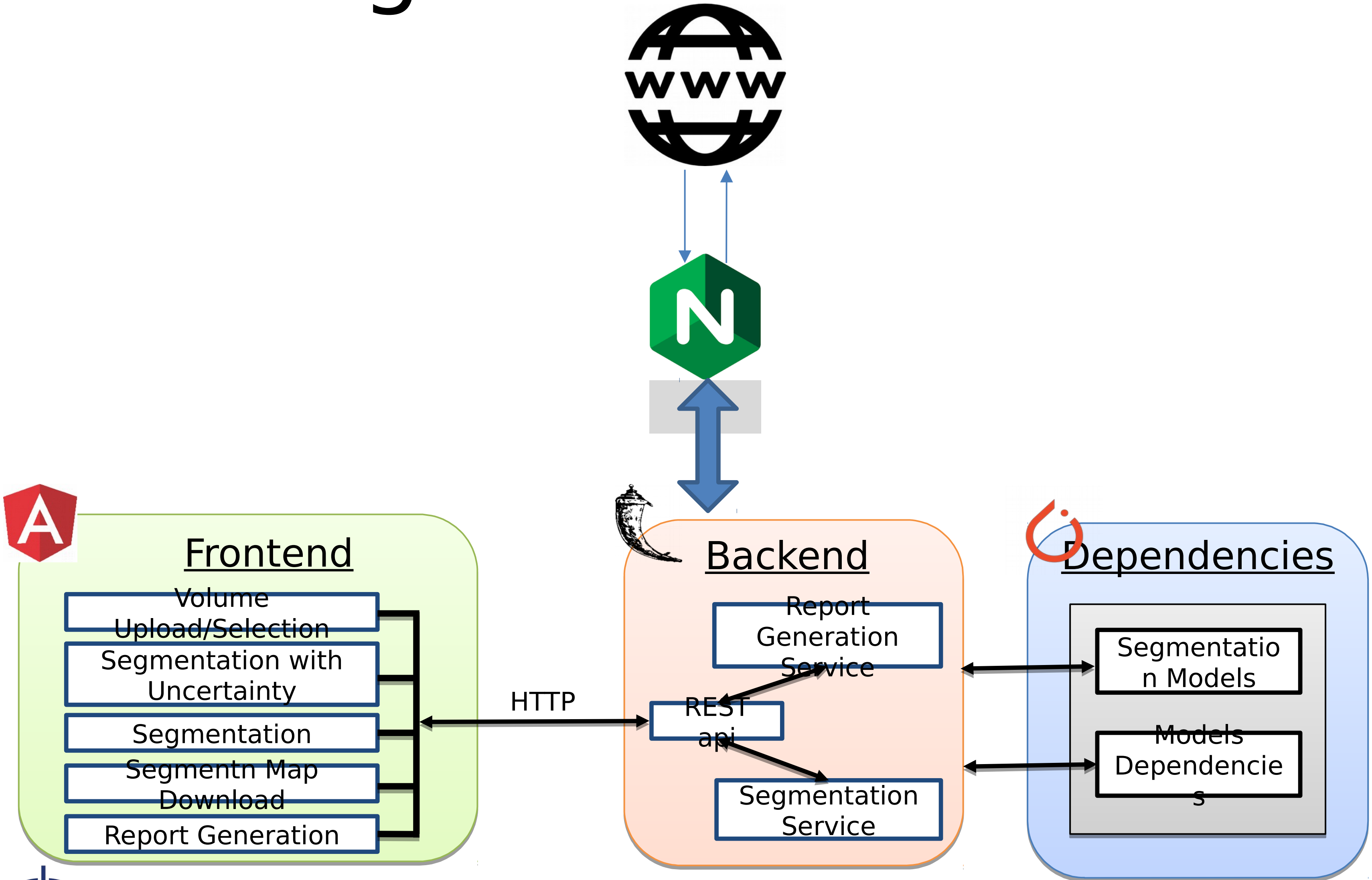
- Dice vs IoU relation in non-dropout models.

Models	Monte-Carlo Dropout	Probabilistic-Net	Hierarchical U-Net	Full Bayesian
Correlation Score	39.6%	50.9%	34.5%	59.2%
Dice vs IoU Plots				

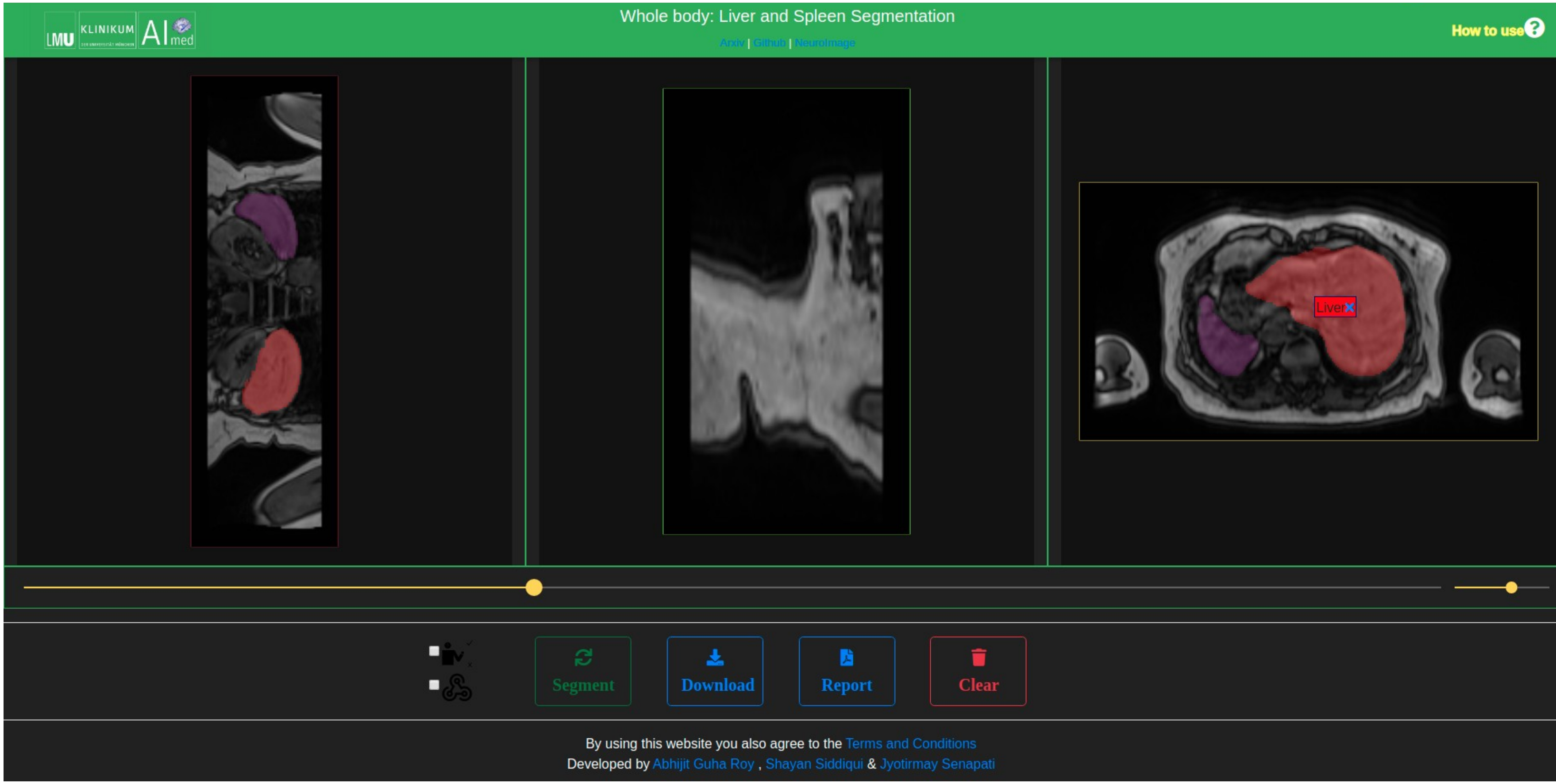
Stage 2: Web App

- Whole-Body segmentation integration.
- Inclusion of Uncertainty measures.
- Report Generation.

Stage 2: Architecture



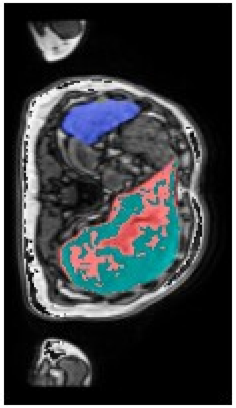
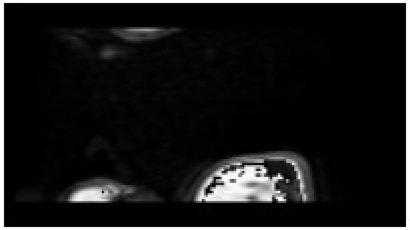
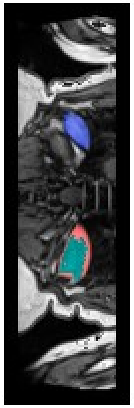
Stage 2: Whole Body Seg Outputs



Stage 2: Brain Segmentation Report

AI-Med Report
01/07/2020

Lab for Artificial Intelligence in Medical Imaging
Waltherstr. 23
80337 München

Whole Body Matter Percentage with model Uncertainty

ID	Structure	Vol*	%ICV	U*	
1	Spleen	21922	6.59	0.15	

ID	Structure	Vol*	%ICV	U*	
2	Liver	118944	35.74	0.09	

Stage 2: Demo

http://abdomen.ai-med.de

Stage 3: Clinical Analysis for Diabetes

Perform clinical analysis to identify possible imaging bio-markers relating to early onset of diabetes.

Datasets:

- KORA Diabetes Diagnosis
- UK Bio-Bank Diabetes Diagnosis

Preprocessing:

- Drop highly uncertain segmentations(IoU<0.51)

Methodologies:

- Regressing Segmentation Volume.
- Classifying Diabetes State.
- Transfer Learning.

Stage 3: Regression Models

- Raw Model *(Type I)*

- Raw Model *(Type I)*

$$Volume = a_0 + * a_1 * Age + a_2 * BMI + a_3 * Sex + a_4 * DiabetesStatus + err$$

- Use of Uncertainty as confounder *(Type II)*

- Use of Uncertainty as confounder *(Type II)*

$$Volume = a_0 + * a_1 * Age + a_2 * BMI + a_3 * Sex + a_4 * DiabetesStatus + a_5 * Uncertainty + err$$

- Use of Uncertainty as instance weights *(Type III)*

- Use of Uncertainty as instance weights *(Type III)*

$$Uncertainty * (Volume \sim a_0 + * a_1 * Age + a_2 * BMI + a_3 * Sex + a_4 * DiabetesStatus + err)$$

Stage 3: Regression Outputs

	Type I	Type II	Type III
Dataset(KORA)	0.009	--	--
Monte-Carlo dropout	0.014	0.011	0.012
Probabilistic U-net	0.016	0.010	0.016
Hierarchical U-net	0.019	0.014	0.019
Full-bayesian	**0.053**	0.021	0.048

Table shows p-value significance scores of diabetes status to various linear model with or without the inclusion of uncertainty.

Stage 3: Classification Models

- Raw Model *(Type I)*

- Raw Model *(Type I)*

$$DiabetesStatus = a_0 + * a_1 * Age + a_2 * BMI ** 2 + a_3 * Sex + a_4 * Volume + err$$

- Use of Uncertainty as confounder *(Type II)*

- Use of Uncertainty as confounder *(Type II)*

  - $DiabetesStatus = a_0 + * a_1 * Age + a_2 * BMI ** 2 + a_3 * Sex + \boldsymbol{a_4} * \boldsymbol{Volume} + \boldsymbol{a_5} * \boldsymbol{IoU} + err$
  - $DiabetesStatus = a_0 + * a_1 * Age + a_2 * BMI ** 2 + a_3 * Sex + \boldsymbol{a_4} * \boldsymbol{Uncertainty} * \boldsymbol{Volume} + err$

- Use of Uncertainty as instance weights *(Type III)*

- Use of Uncertainty as instance weights *(Type III)*

$$Uncertainty * (DiabetesStatus = a_0 + * a_1 * Age + a_2 * BMI ** 2 + a_3 * Sex + a_4 * Volume + err)$$

Stage 3: Classification Outputs

	Type I	Type II-1	Type II-2	Type III
Monte-Carlo dropout	0.81403	0.81421	**0.81691**	0.80393
Probabilistic U-net	0.81565	0.81709	**0.81818**	0.80970
Hierarchical U-net	0.81295	0.81439	**0.81583**	0.80681
Full-bayesian	0.81421	**0.81619**	0.81097	0.80916

Table shows AUC-score for various linear model with or without the inclusion of Uncertainty on a validation set from same dataset i.e. KORA.

Stage 3: Cross Dataset Classification

	Type I	Type II-1	Type II-2	Type III
Monte-Carlo dropout	0.71242	0.70164	0.69994	**0.72018**
Probabilistic U-net	0.70784	0.66972	0.68065	**0.71268**
Hierarchical U-net	0.69971	0.67642	0.68453	**0.70949**

Table shows AUC-score for various linear model with or without the inclusion of
Uncertainty on a test set from different dataset i.e. UK-Biobank.

Stage 3: Other Findings

- Significant volume differences between diabetic and non-diabetic ground truth and inferenced segmentation.

	Normal vs Diabetic Volume Differences	
	Liver Volume	Spleen Volume
Dataset(KORA)	**1.01e-05**	0.014
Monte-Carlo dropout	**1.90e-06**	0.111
Probabilistic U-net	**1.05e-05**	0.116
Hierarchical U-net	**3.35e-06**	0.239
Full Bayesian	**3.84e-05**	0.132

Table shows significance volume difference between normal and diabetic liver volume compare to spleen volume.

Discussion

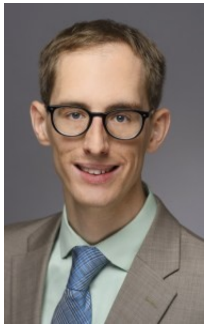
Future Work

- Exploration of Multi-Mode Segmentation
- 3D Segmentation Strategies.
- Statistical Analysis with more features.

Thank You and Questions

A special thanks to

Abhijit Guha Roy
Google Health, London



Dr. Sebastian Pölsterl
AI-Med, LMU Klinikum

Prof. Dr. Christian Wachinger
AI-Med, LMU Klinikum

Prof. Dr. Nassir Navab
CAMP, TUM

Technische Universität München + Johns Hopkins Whiting School of Engineering