
Integration of Structural and Diffusion Metrics in Fetal MRI: A Model to Support Clinical Evaluation

Presenter: Javier Muñoz

Supervised by: Prof. Dr.-Ing. Jana Hutter & M.Sc. Nyvenn de Castro

Master's Thesis in Medical Engineering

April 17th 2025

Erlangen, Germany

Integration of Structural and Diffusion Metrics in Fetal MRI

Camila's Story....



Integration of Structural and Diffusion Metrics in Fetal MRI

Camila's Story....



Integration of Structural and Diffusion Metrics in Fetal MRI

Camila's Story....



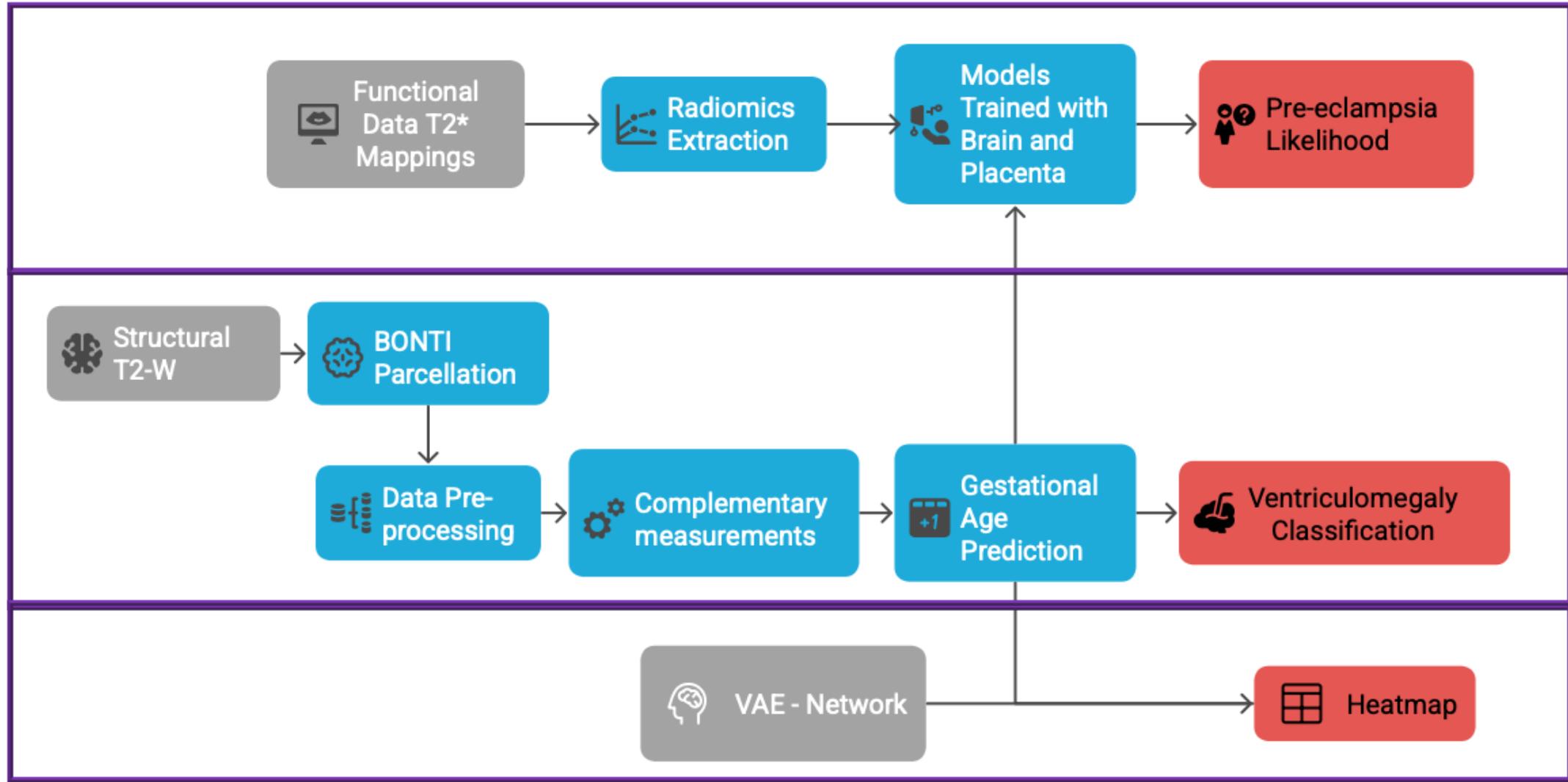
Integration of Structural and Diffusion Metrics in Fetal MRI

Camila's Story....

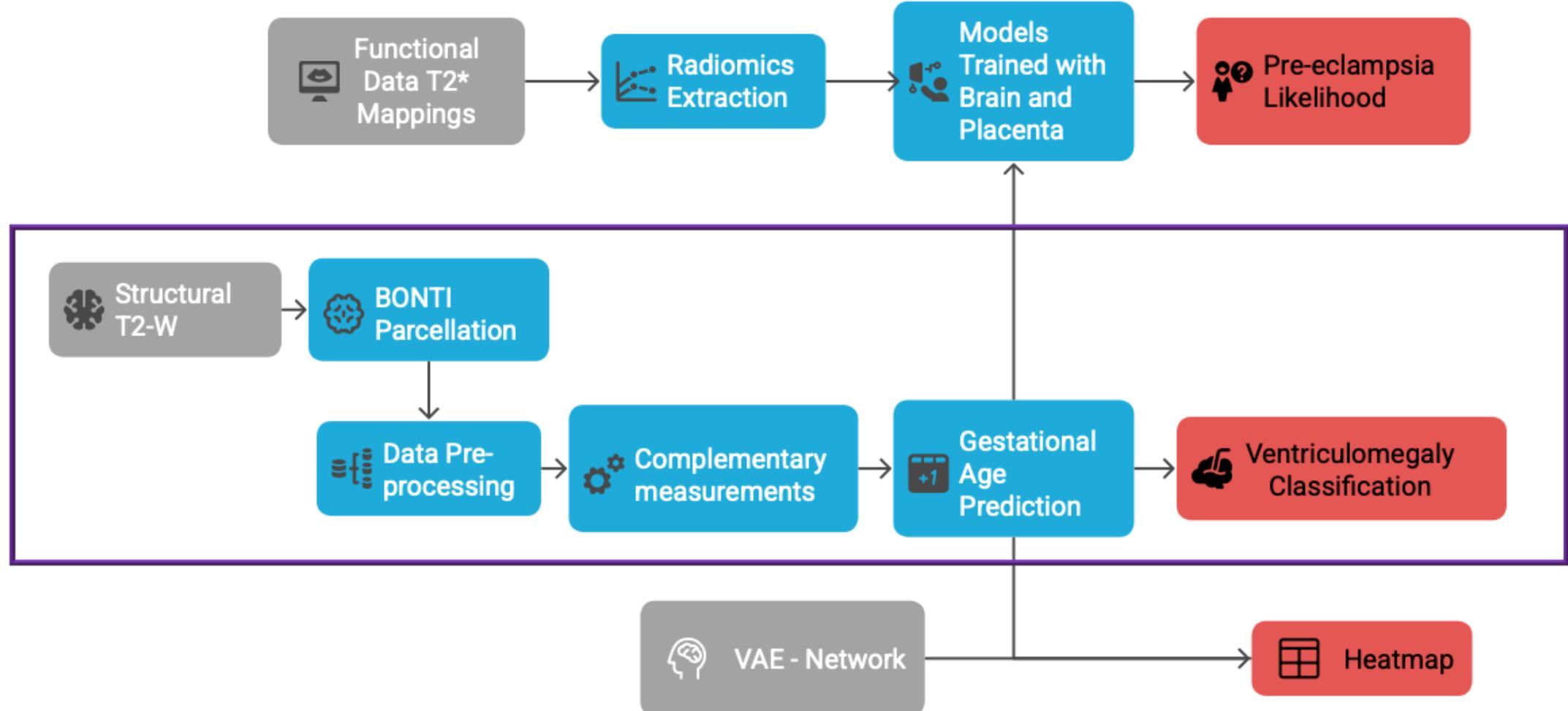


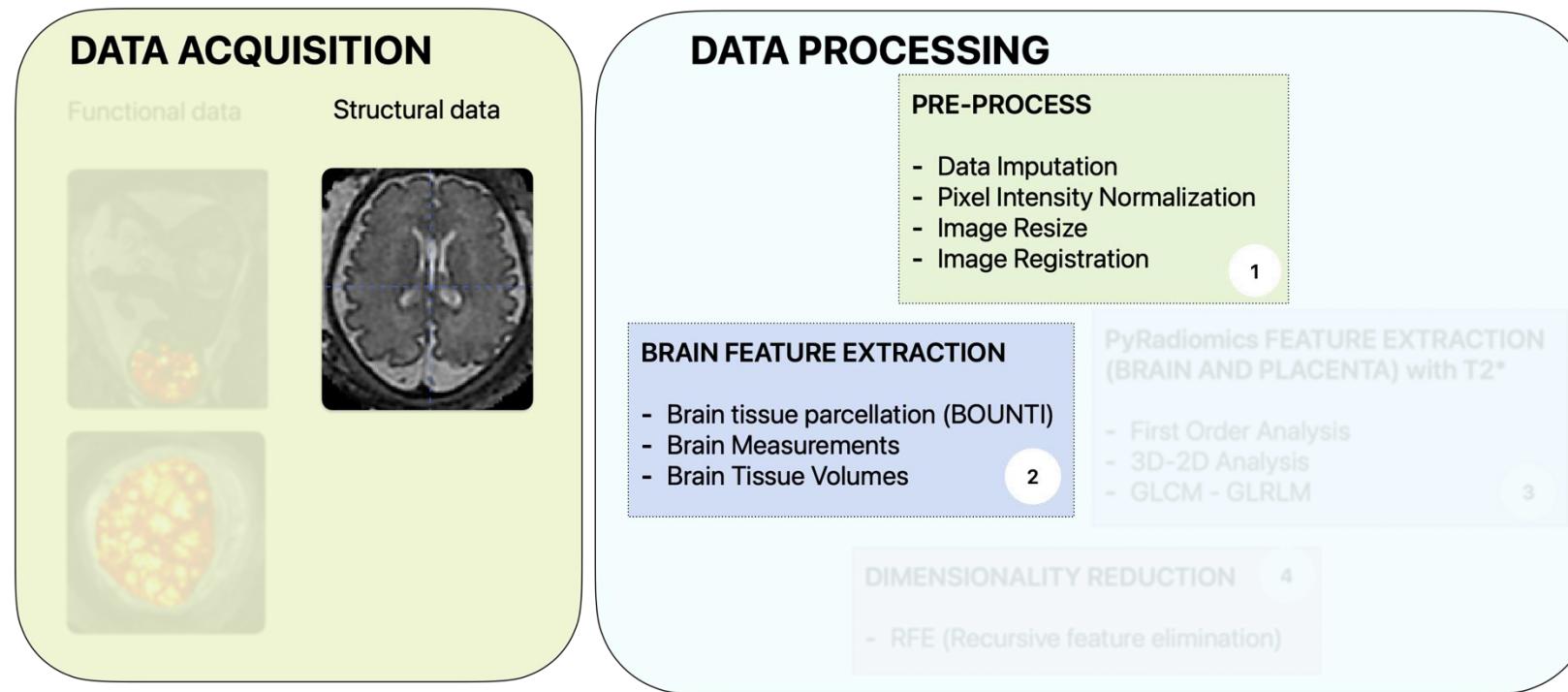
General Pipeline

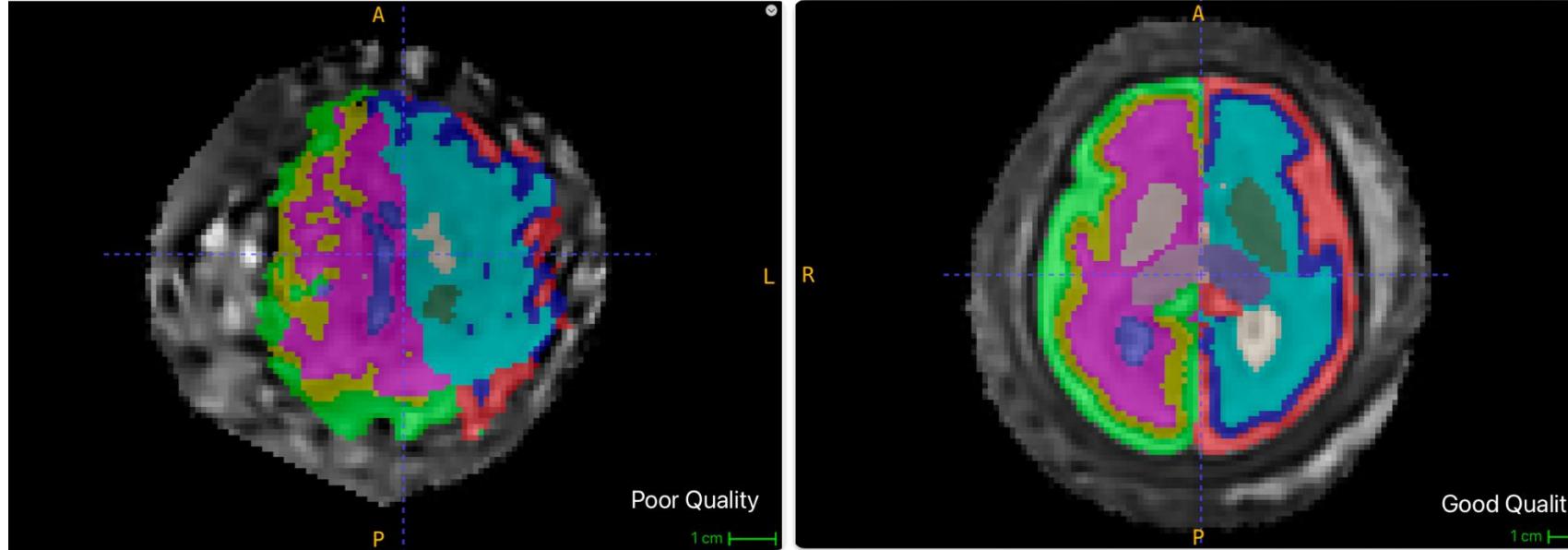
General Pipeline



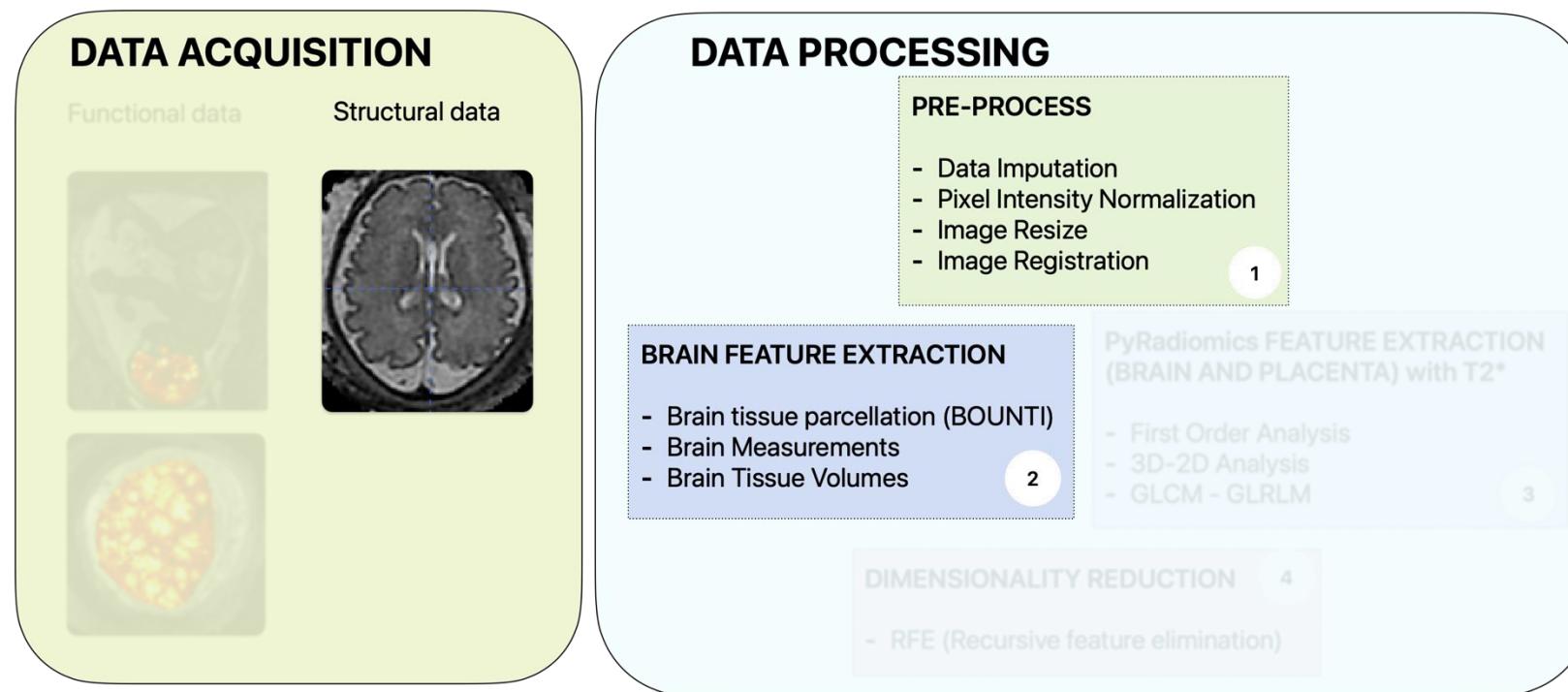
Structural T2 weighted

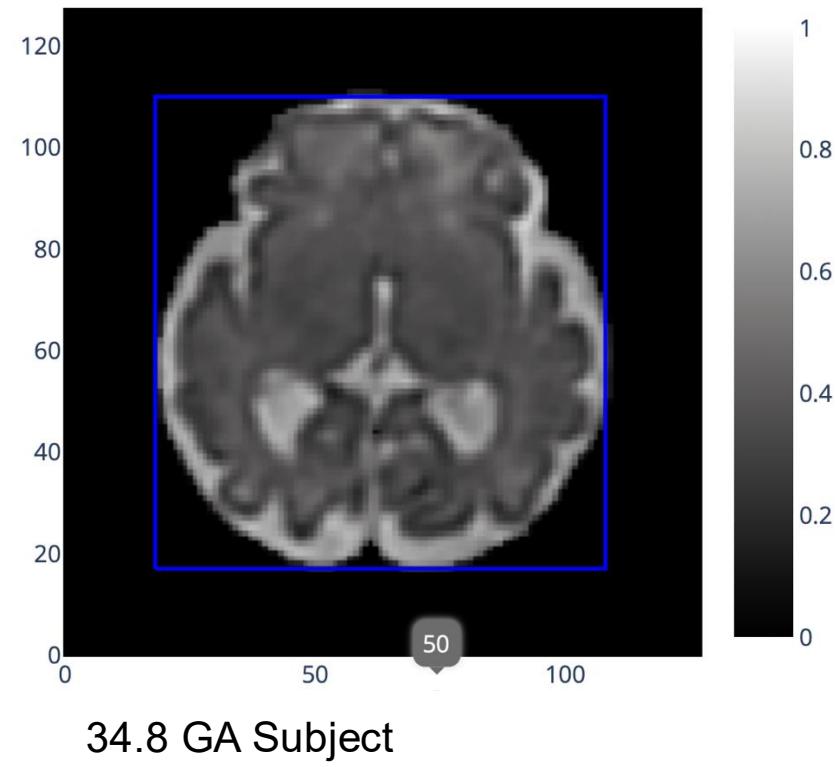






- BOUNTI generates 19 parcellation areas inside the brain
- T2-w Pixel intensity inside range $0 \leq P_i \leq 1$
- Image resizing with SimpleITK library to preserve orientation, spacing and direction beside the voxel size
- Registration with SimpleITK library translation and rotation



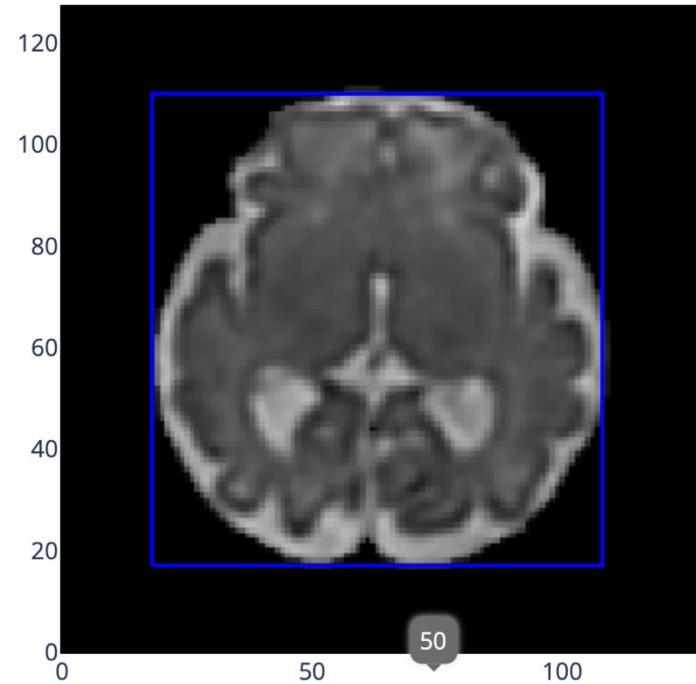


- **Volumes cm³**
- Biparietal Diameter mm
- Head Circumference mm
- Transverse Cerebral Diameter mm
- Cortical Gray Matter cm³
- Parenchyma cm³
- Cerebellum cm³
- Percent Ventricular Asymmetry

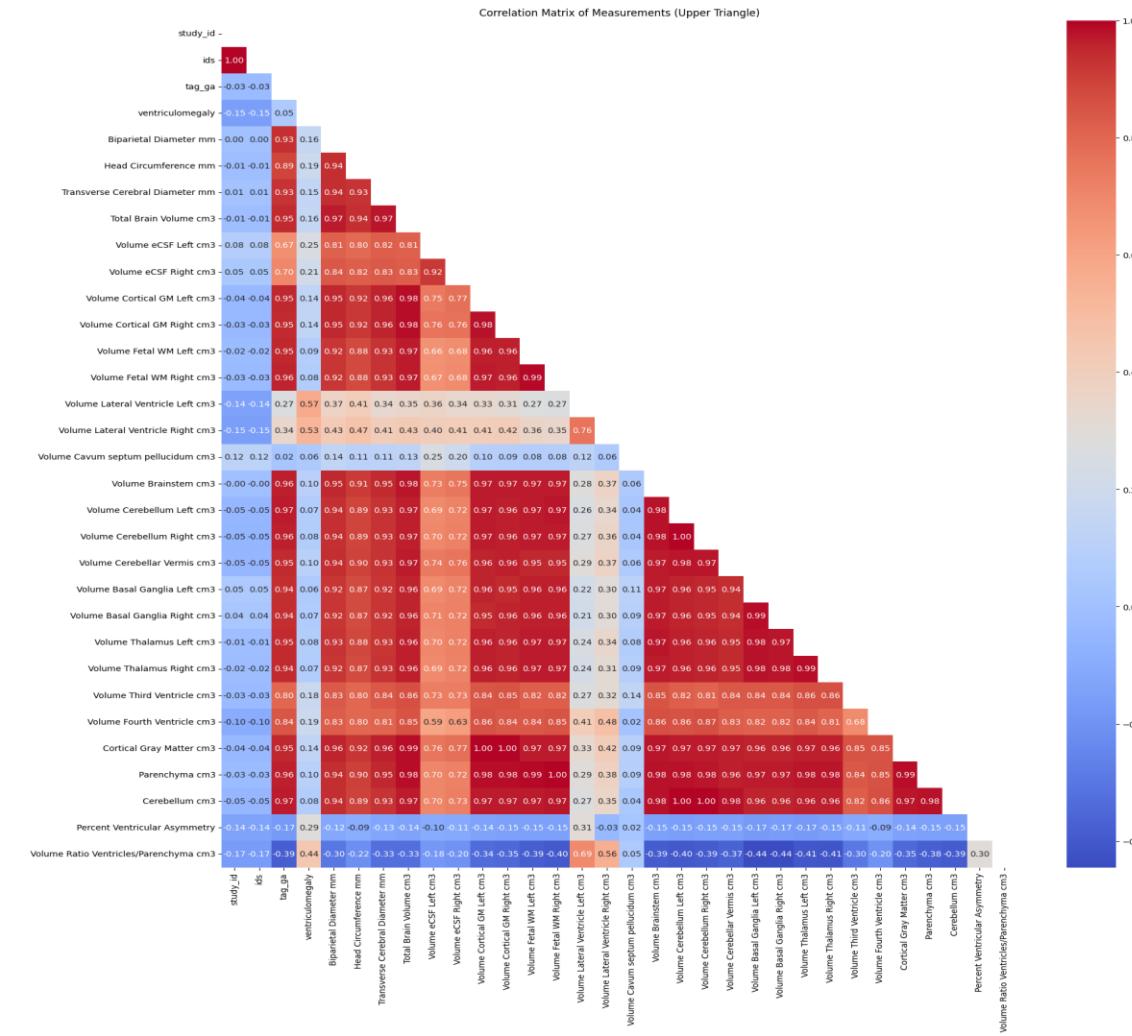
$$PVA = \frac{\max(\text{Left ventricle}, \text{Right ventricle})}{\min(\text{Left ventricle}, \text{Right ventricle})} - 1 * 100$$

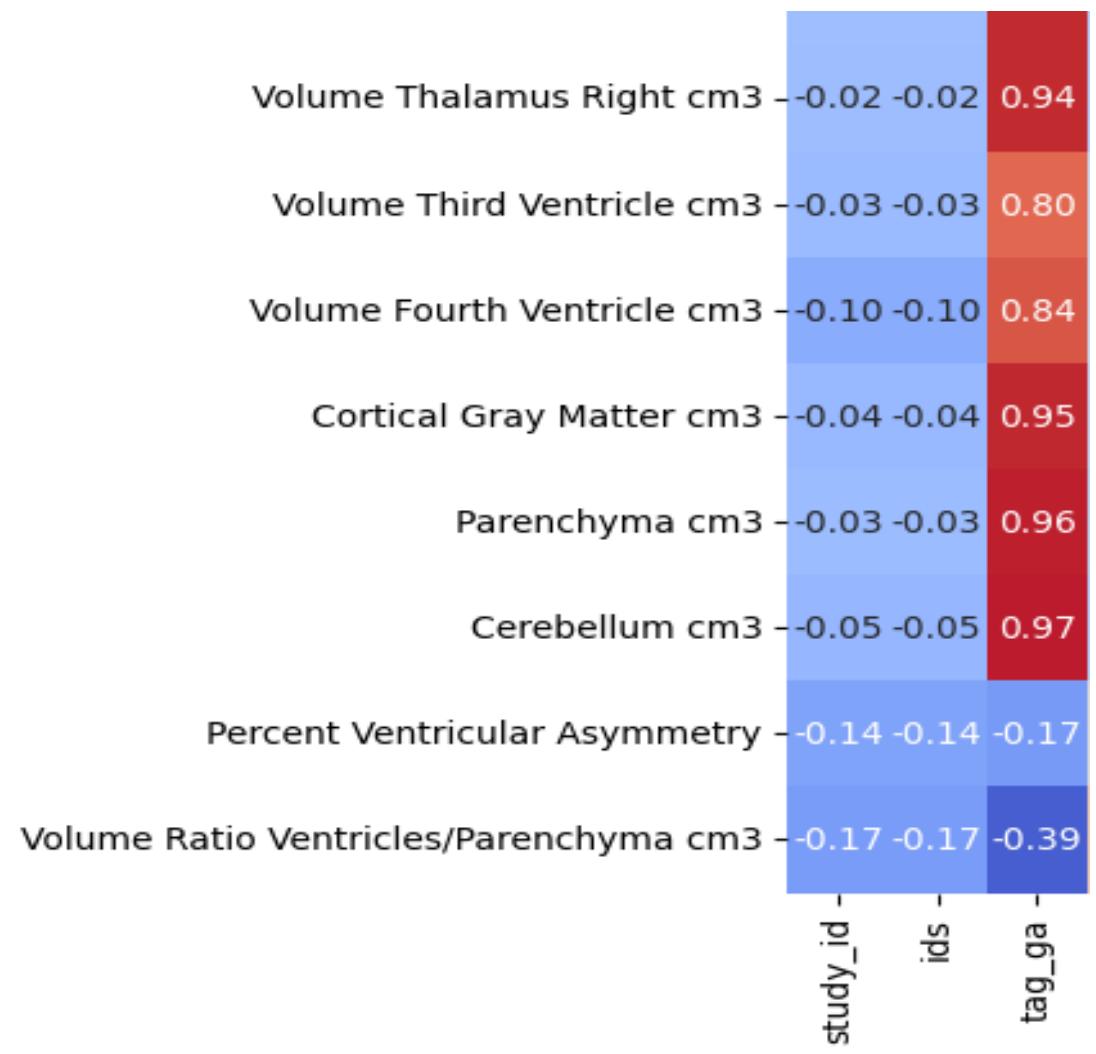
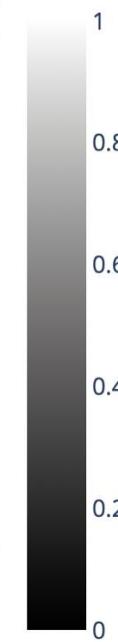
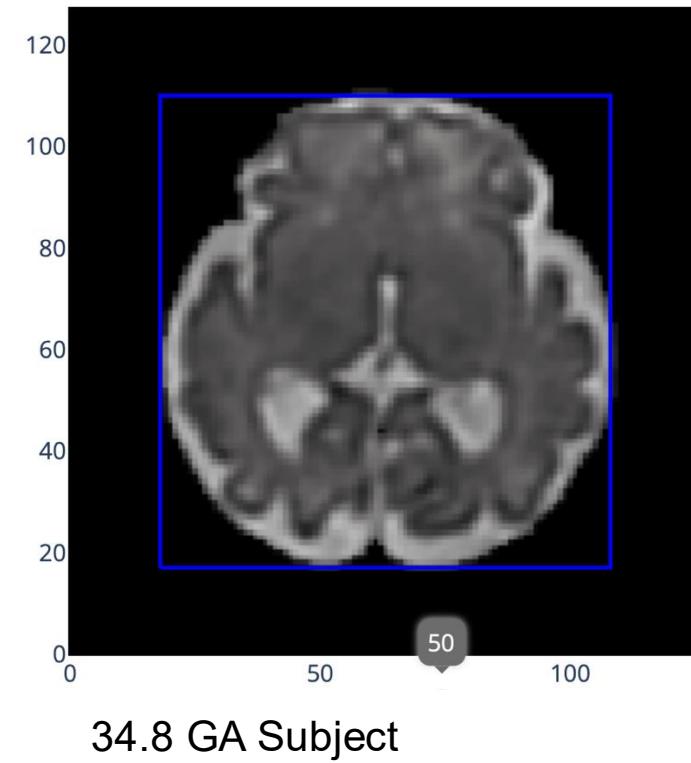
- Volume Ratio Ventricles/Parenchyma cm³

Brain measurements

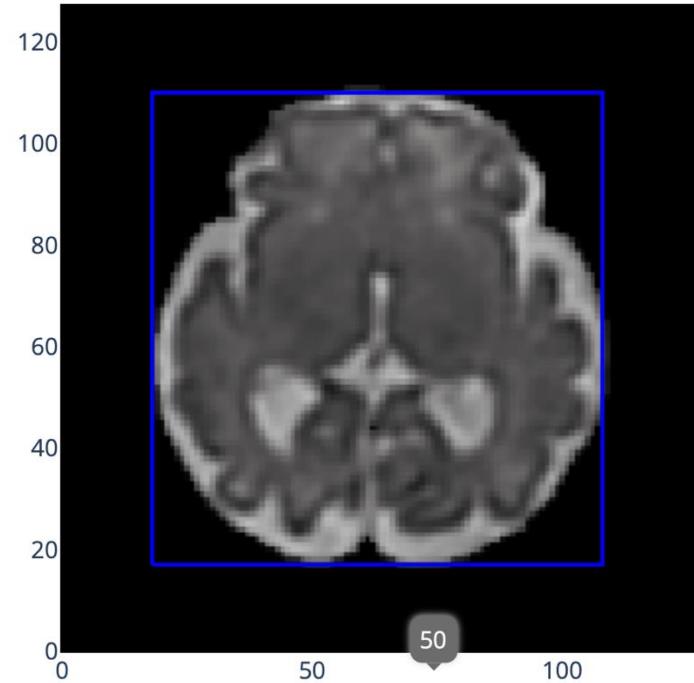


34.8 GA Subject

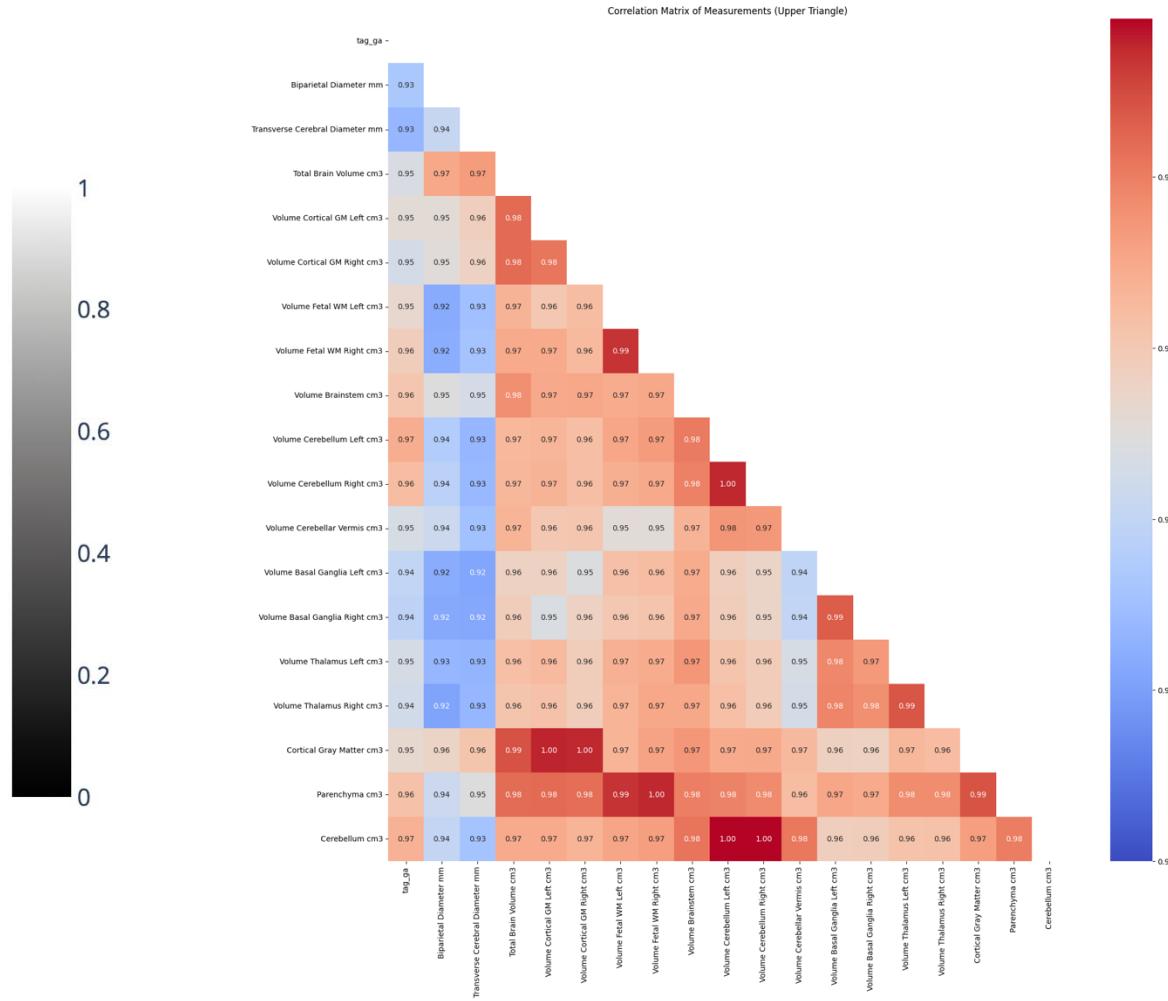




Brain measurements



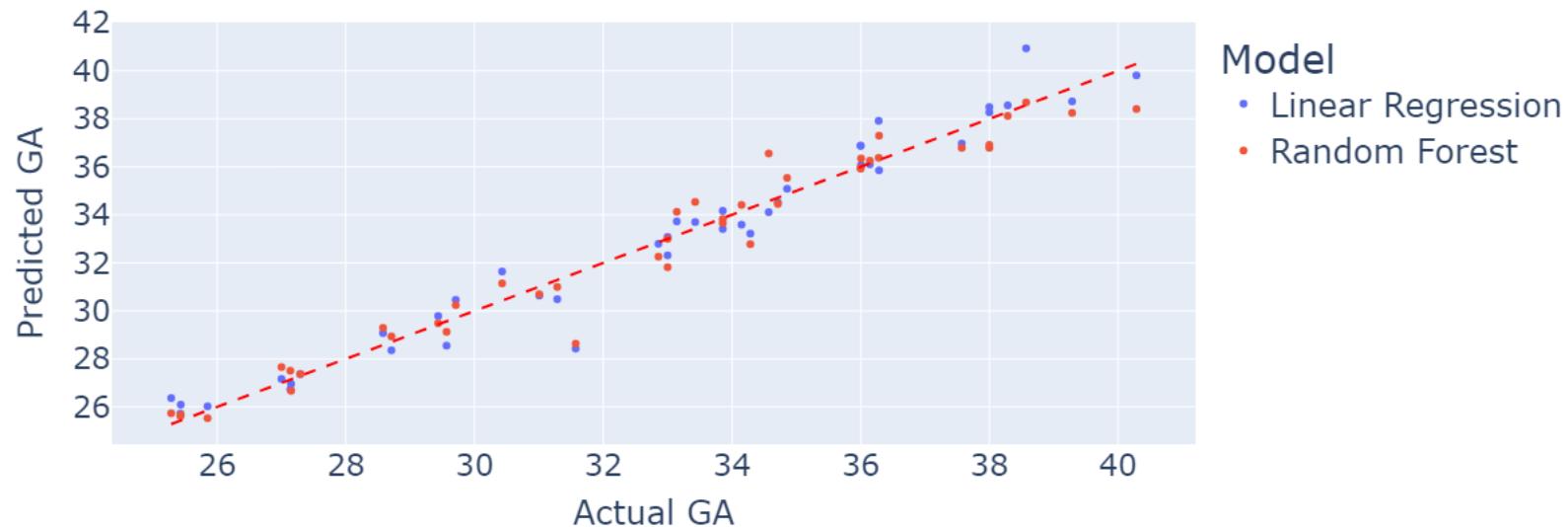
34.8 GA Subject



Model Comparison:

	Model	MAE	MSE	RMSE	R ²
0	Linear Regression	0.606544	0.725109	0.851533	0.95895
1	Random Forest	0.613716	0.748772	0.865316	0.95761

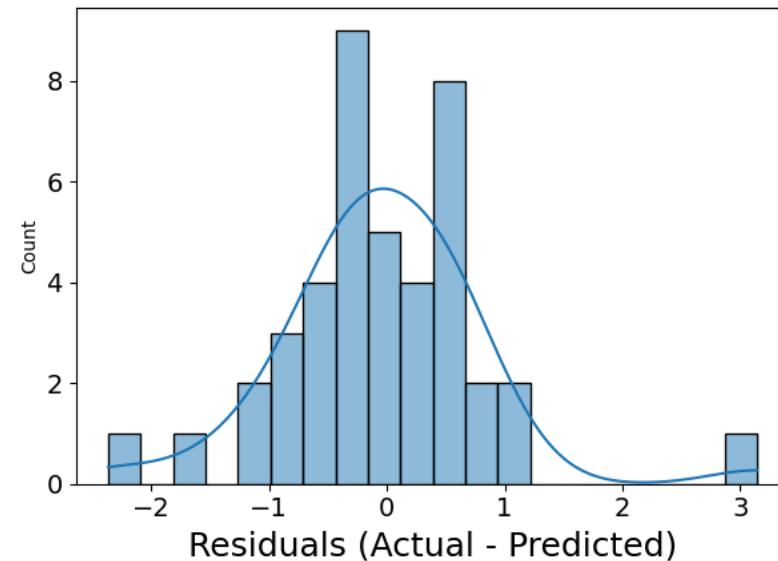
Actual vs. Predicted GA



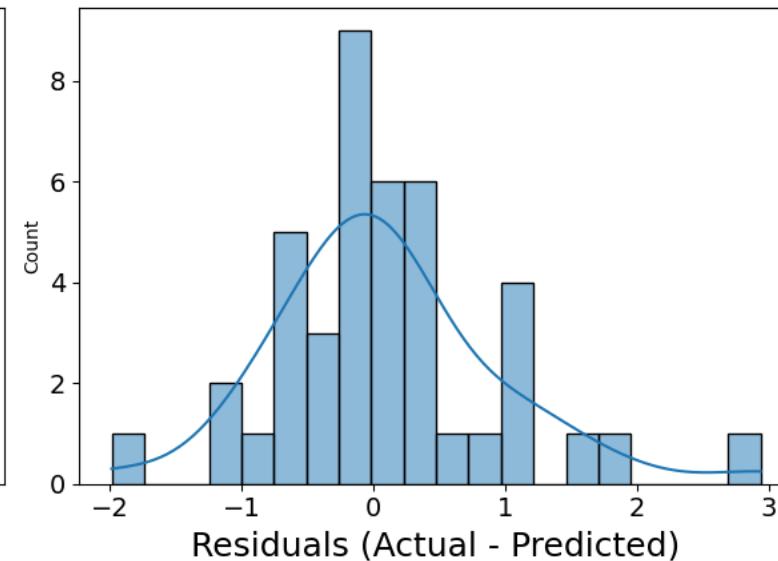
Model Comparison:

	Model	MAE	MSE	RMSE	R ²
0	Linear Regression	0.606544	0.725109	0.851533	0.95895
1	Random Forest	0.613716	0.748772	0.865316	0.95761

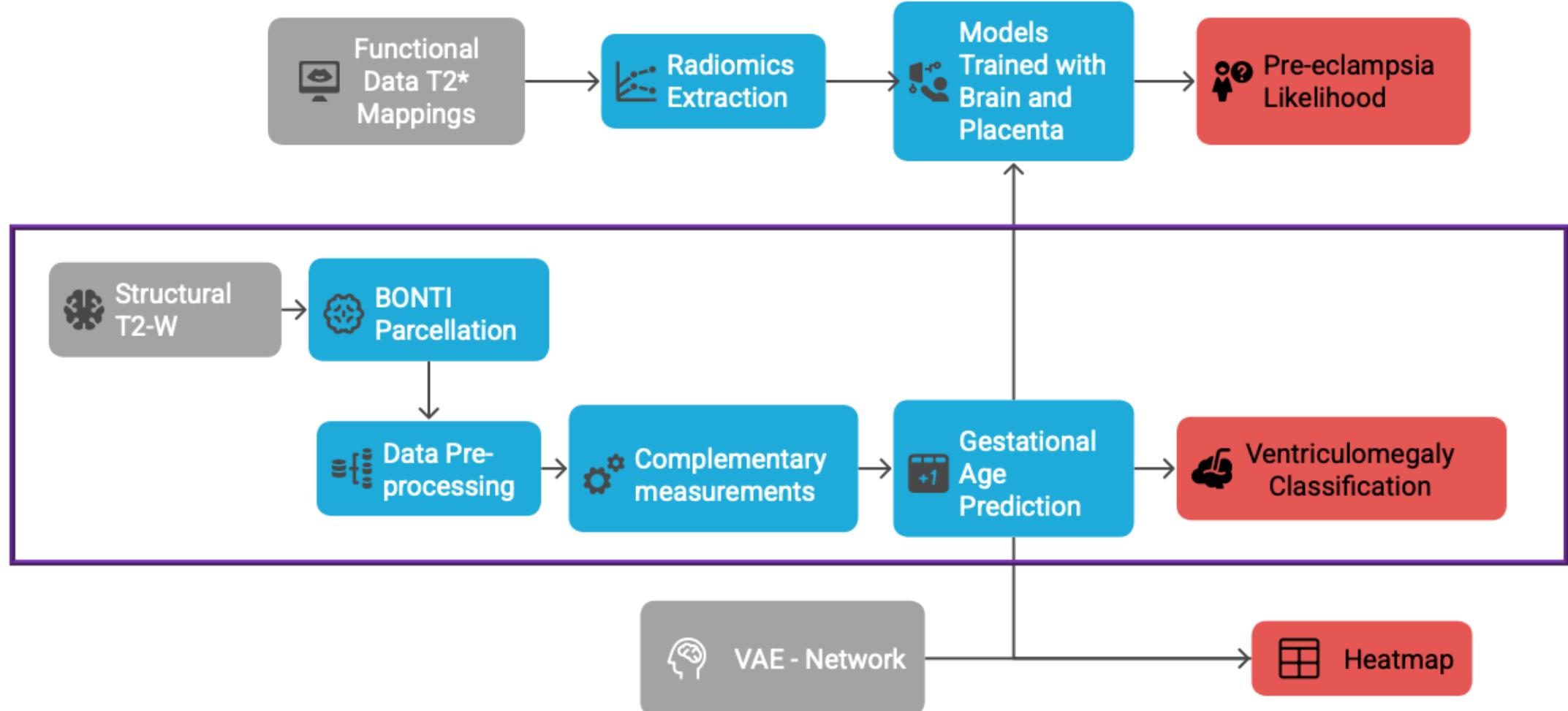
Linear Regression
Skewness = 0.61



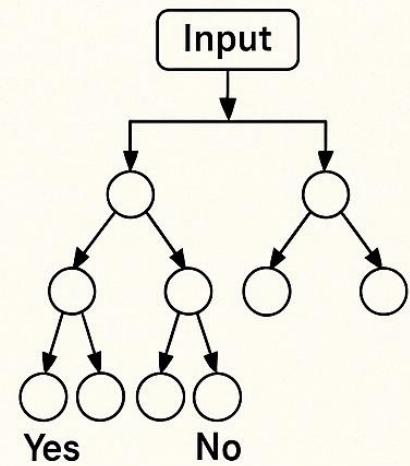
Random Forest
Skewness = 0.77



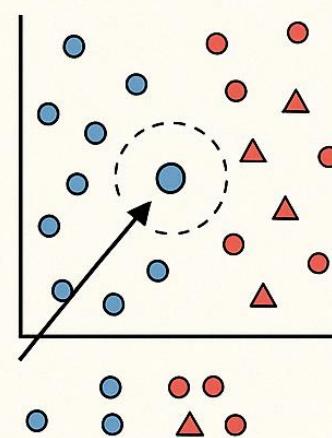
General Pipeline



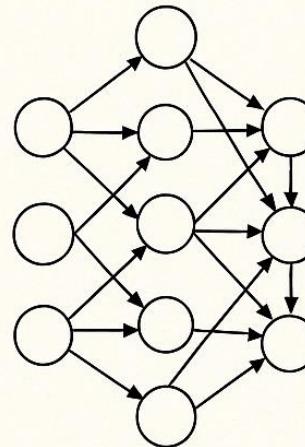
Random Forest



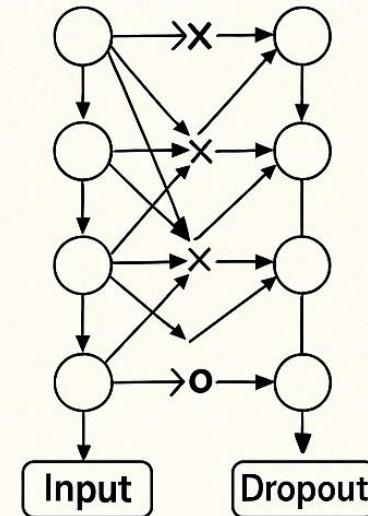
k-Nearest Neighbors



XGBoost



Bayesian Neural Network

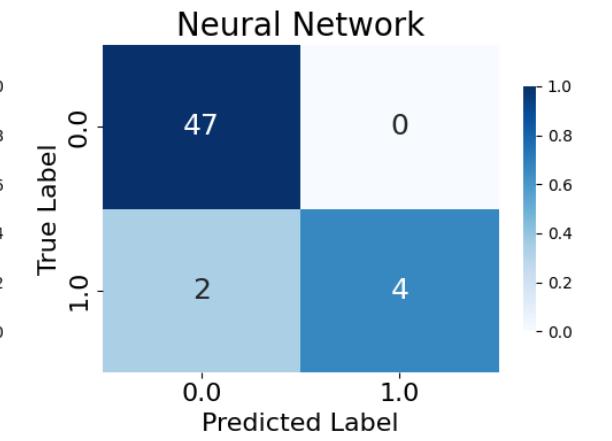
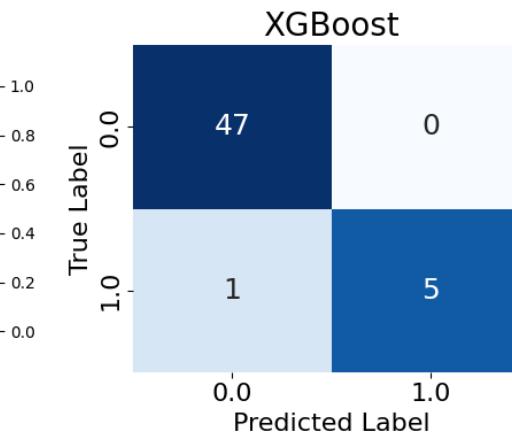
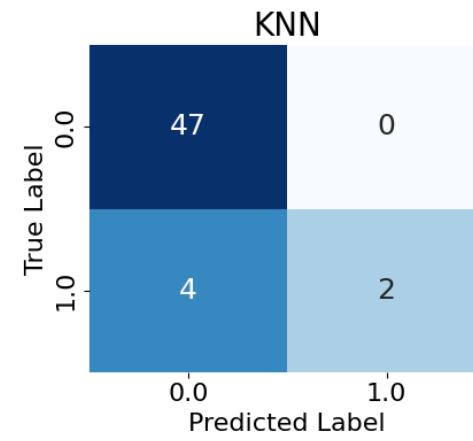
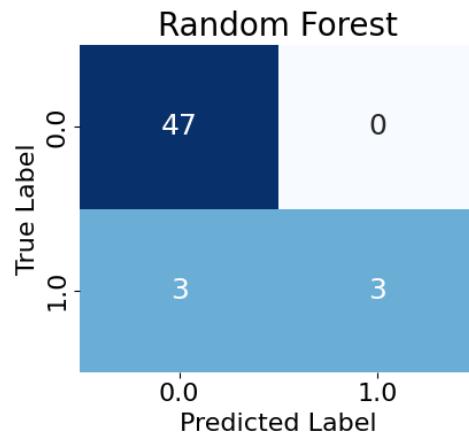


This and all models were trained under the same 4 architectures.

Ventriculomegaly Classification

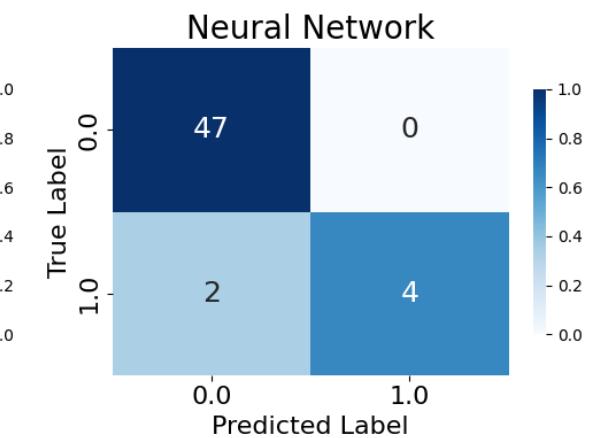
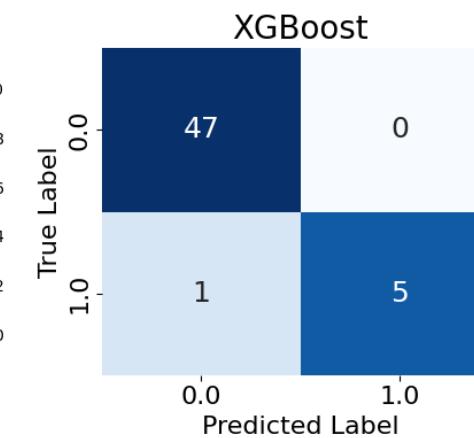
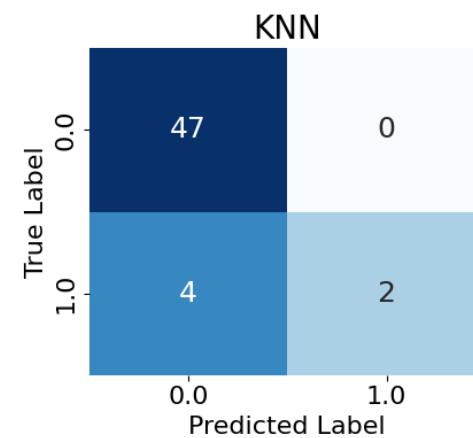
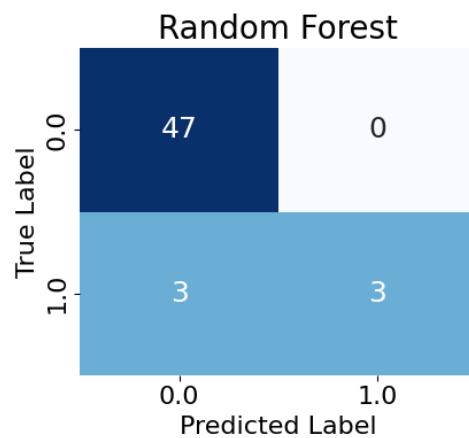
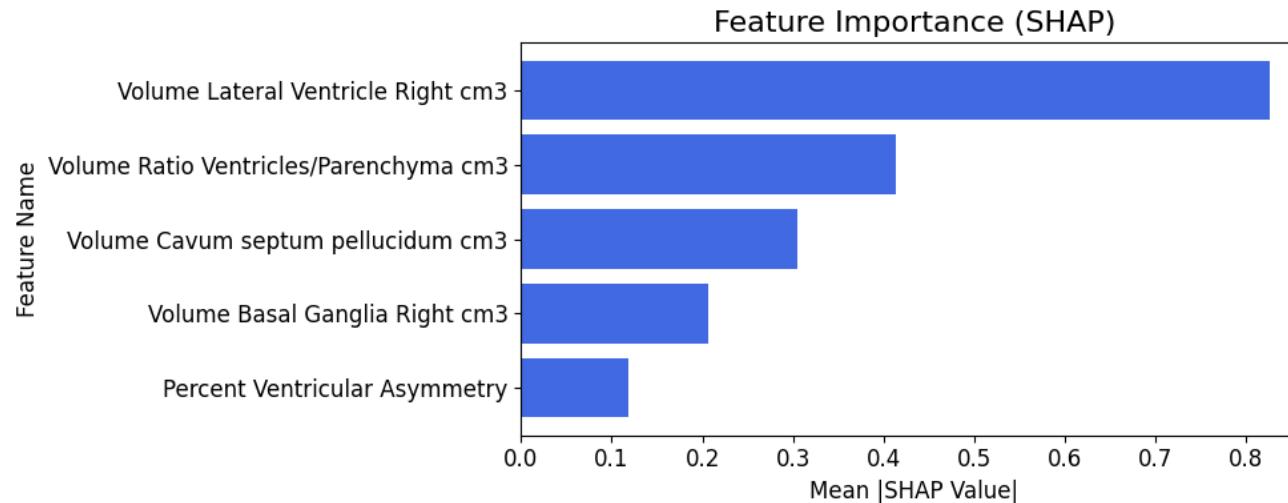
Model Comparison

Model	Accuracy	Precision	Recall	F1 Score
Random Forest	0.962	0.963	0.962	0.958
KNN	0.924	0.930	0.924	0.907
XGBoost	0.981	0.981	0.981	0.980
Neural Network	0.962	0.963	0.962	0.958

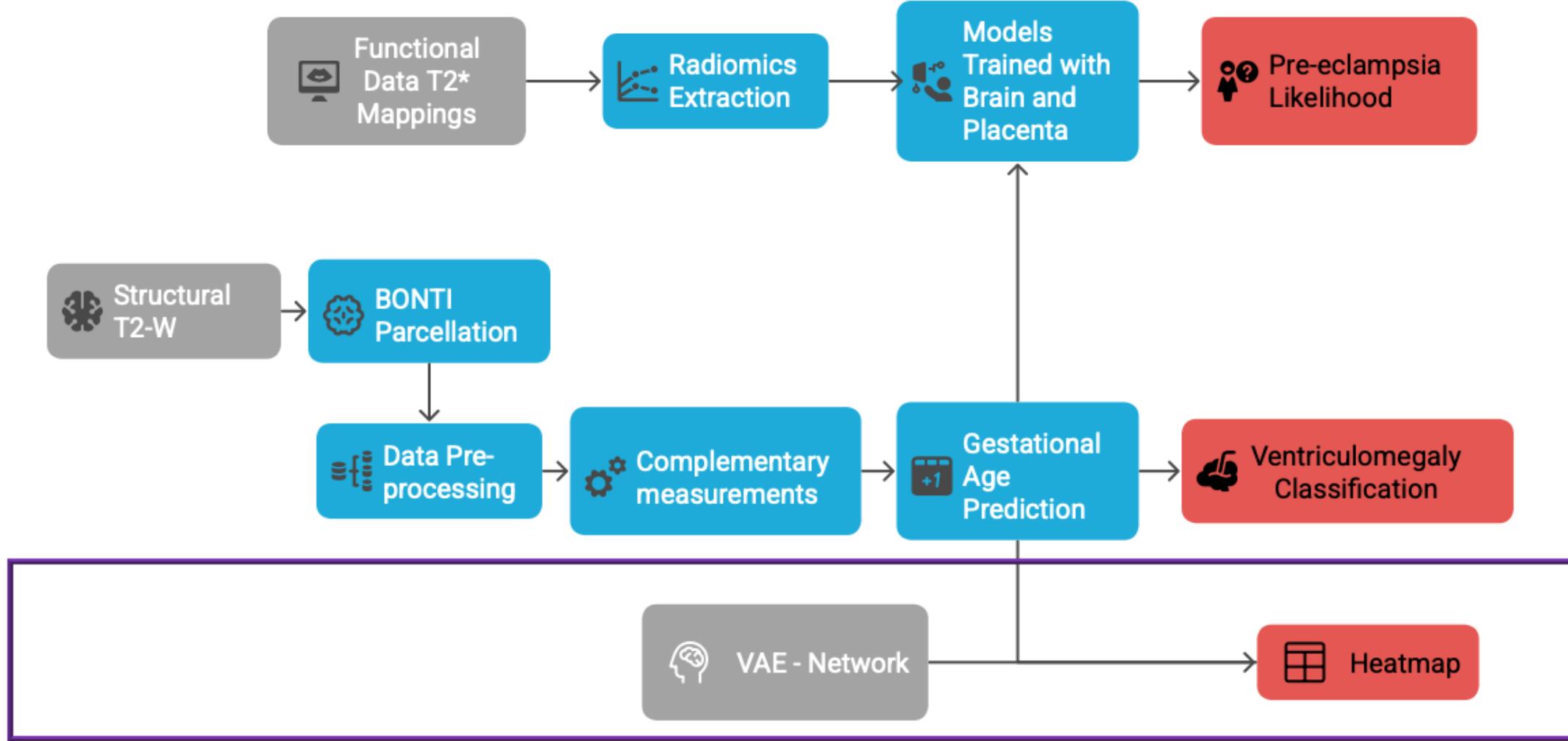


Ventriculomegaly Classification

Which features influence?

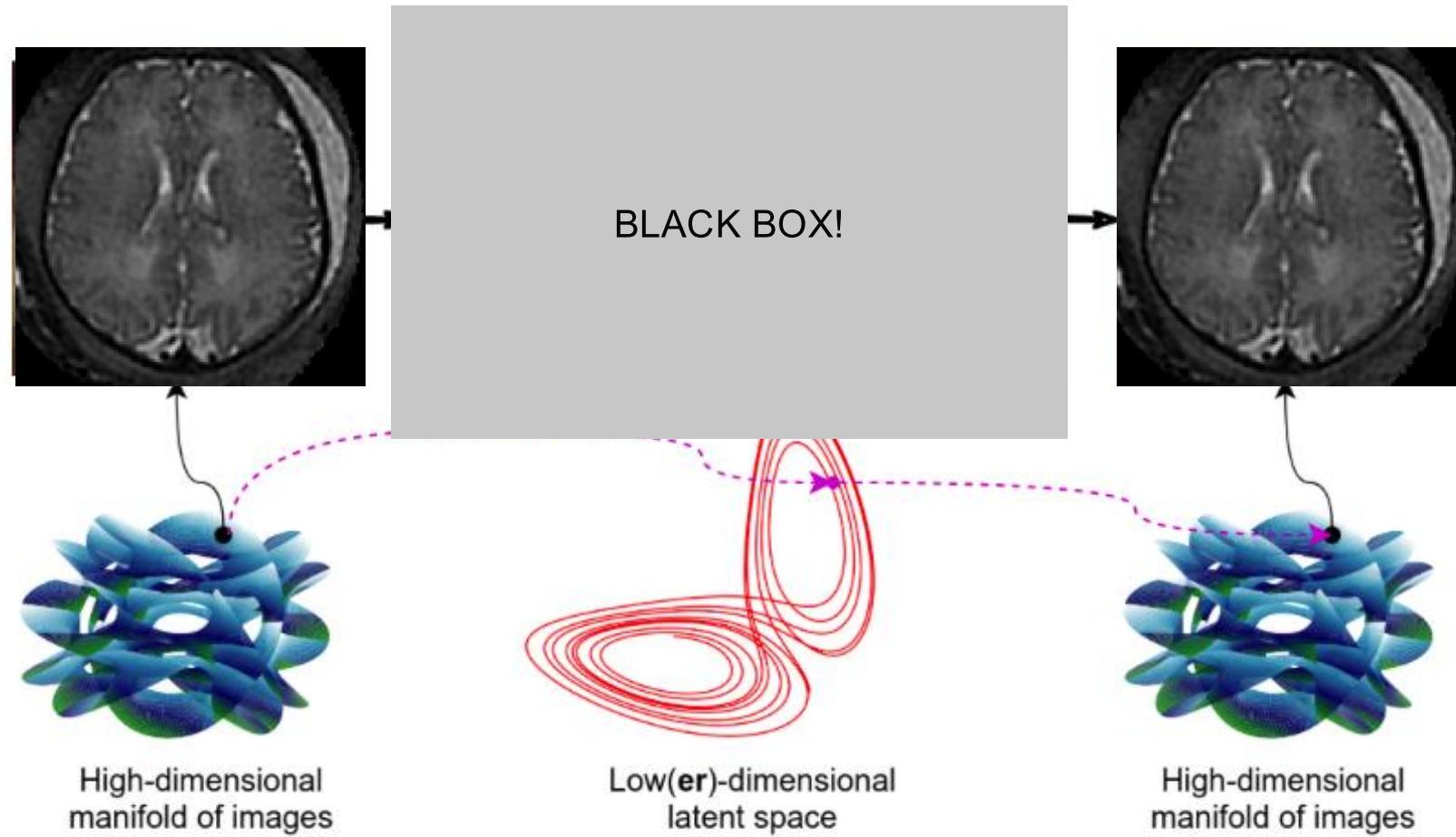


VQ-VAE Heatmap brain abnormalities



Variational Autoencoder

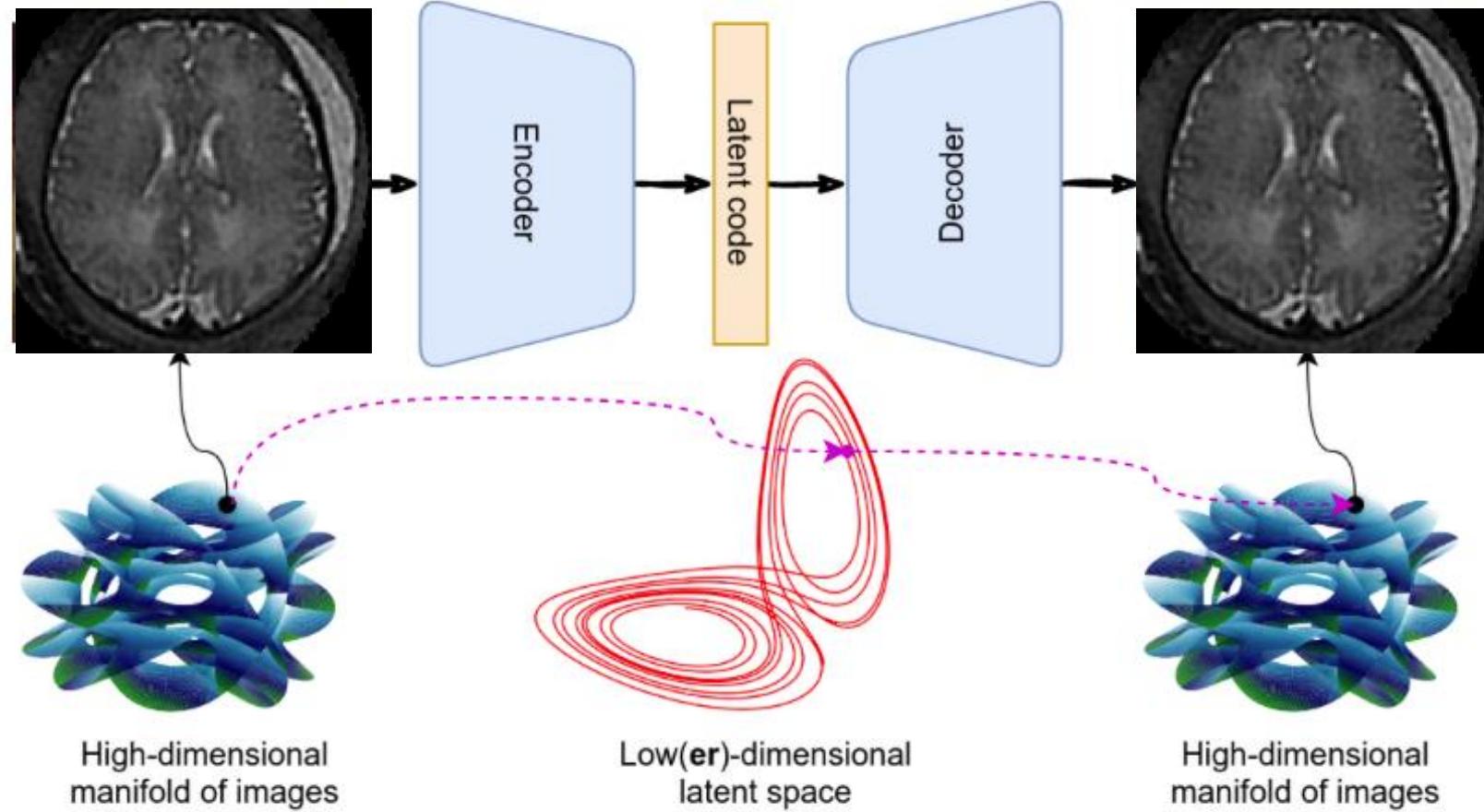
What is a VAE?



[1] Pinaya, Walter H.L., Petru-Daniel Tudosi, Robert Gray, Geraint Rees, Parashkev Nachev, Sébastien Ourselin, and M. Jorge Cardoso. "Unsupervised Brain Imaging 3D Anomaly Detection and Segmentation with Transformers." *Medical Image Analysis* 79 (July 2022): 102475. <https://doi.org/10.1016/j.media.2022.102475>.

Variational Autoencoder

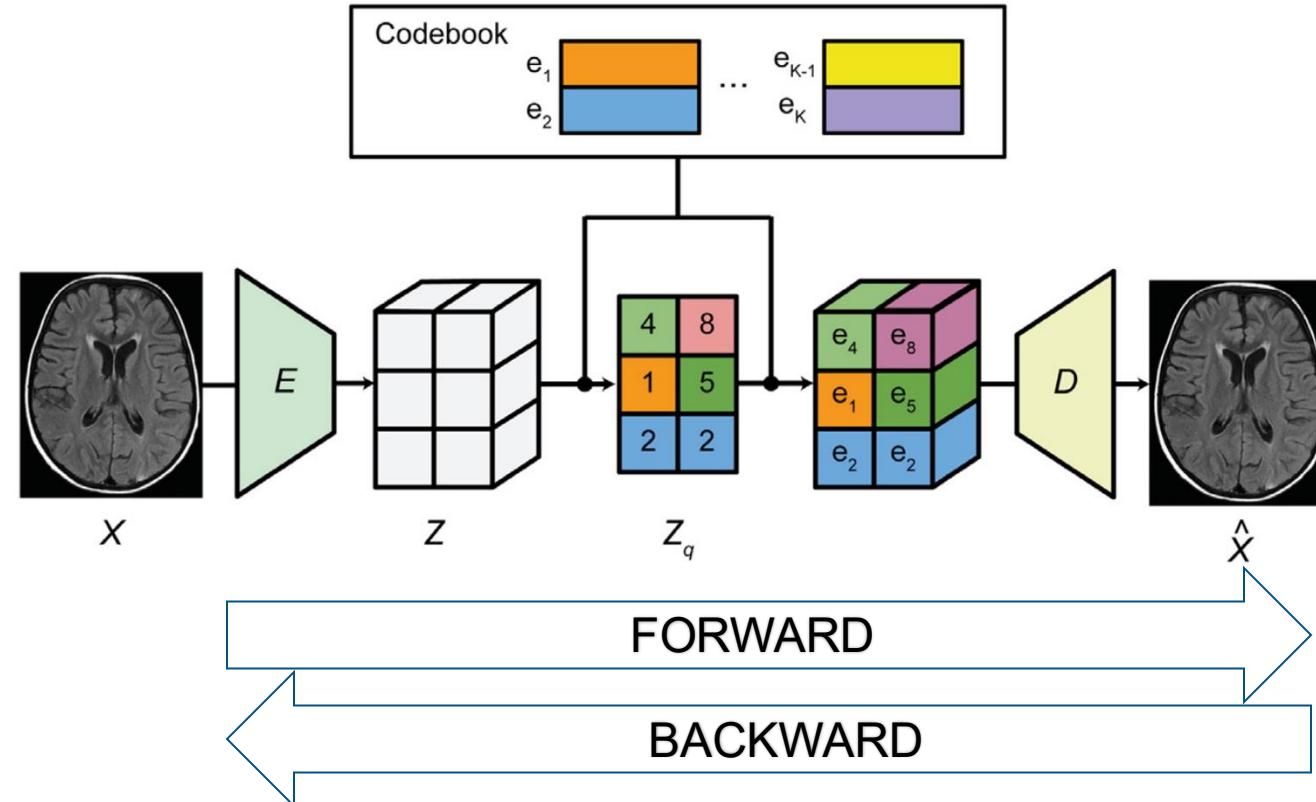
What is a VAE?



[1]

[1] Pinaya, Walter H.L., Petru-Daniel Tudosi, Robert Gray, Geraint Rees, Parashkev Nachev, Sébastien Ourselin, and M. Jorge Cardoso. "Unsupervised Brain Imaging 3D Anomaly Detection and Segmentation with Transformers." *Medical Image Analysis* 79 (July 2022): 102475. <https://doi.org/10.1016/j.media.2022.102475>.

How to perform the output



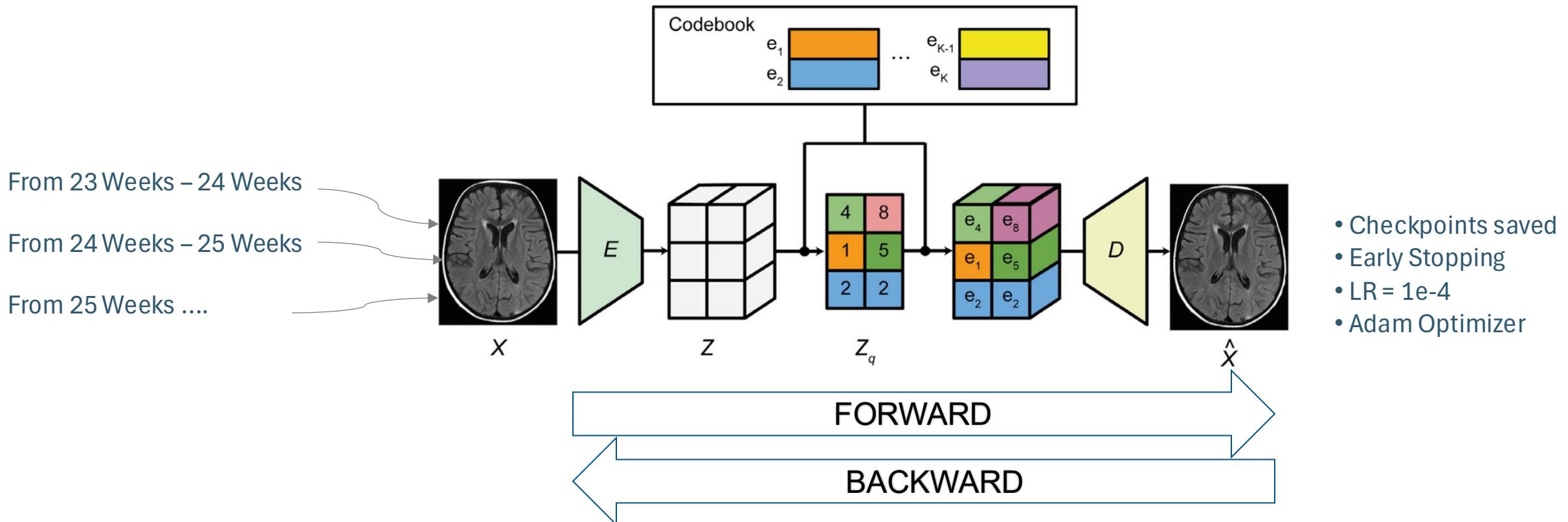
$$\mathcal{L}_{VQ-VAE} = \mathcal{L}_{recons} + \mathcal{L}_{codebook} + \beta \mathcal{L}_{commit}$$

- Checkpoints saved
- Early Stopping
- LR = 1e-4
- Adam Optimizer

How to perform the output



How to perform the output



VQ-VAE Model Output

Heatmap of ventriculomegaly positive case

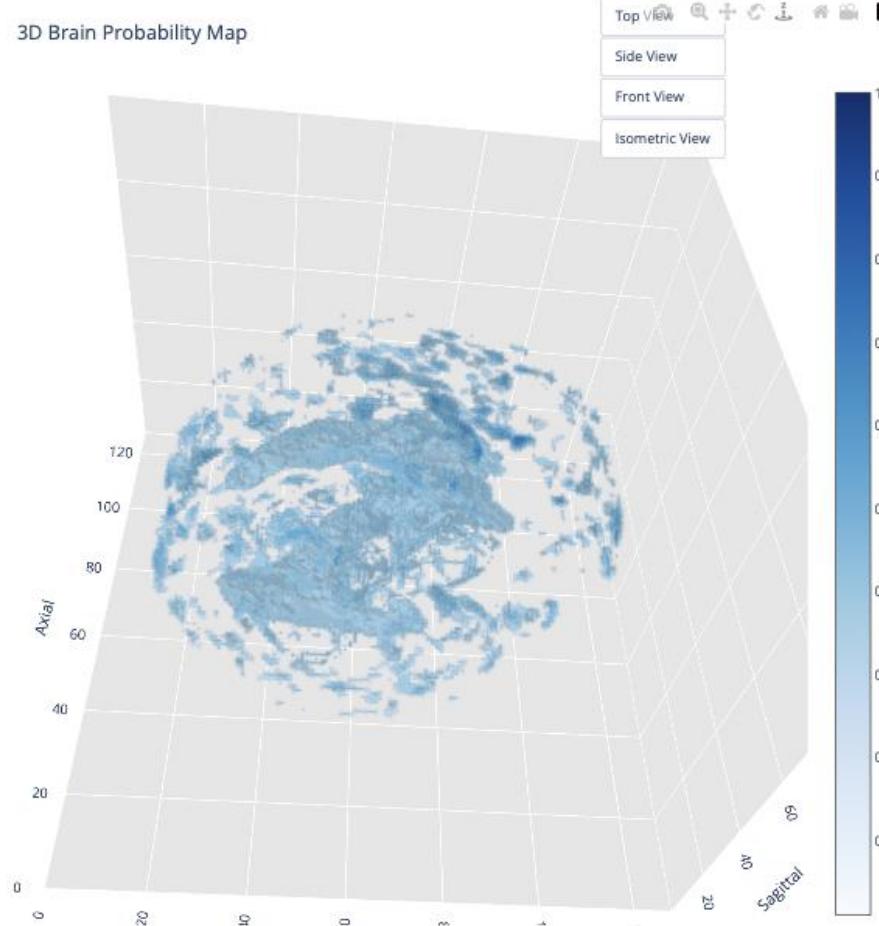
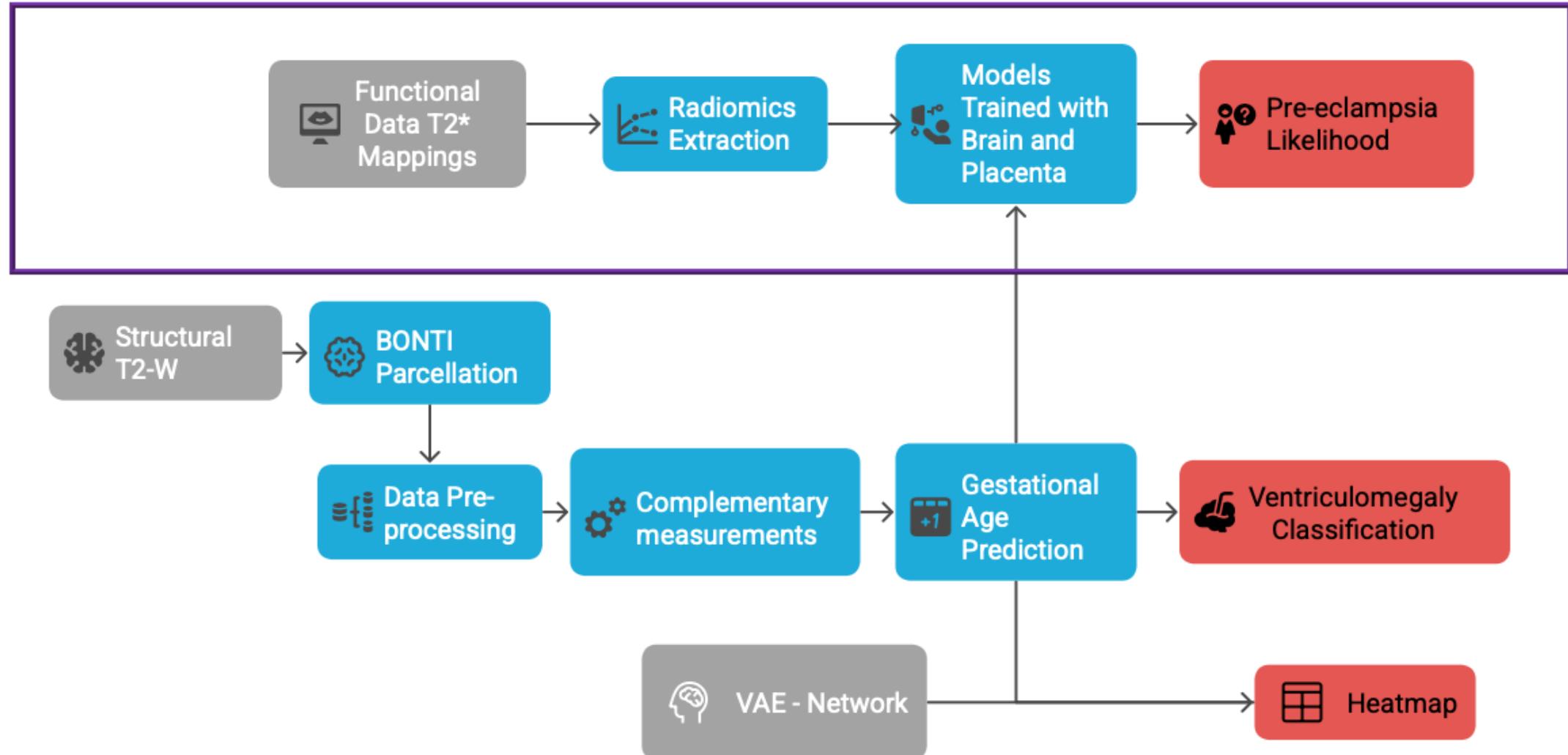


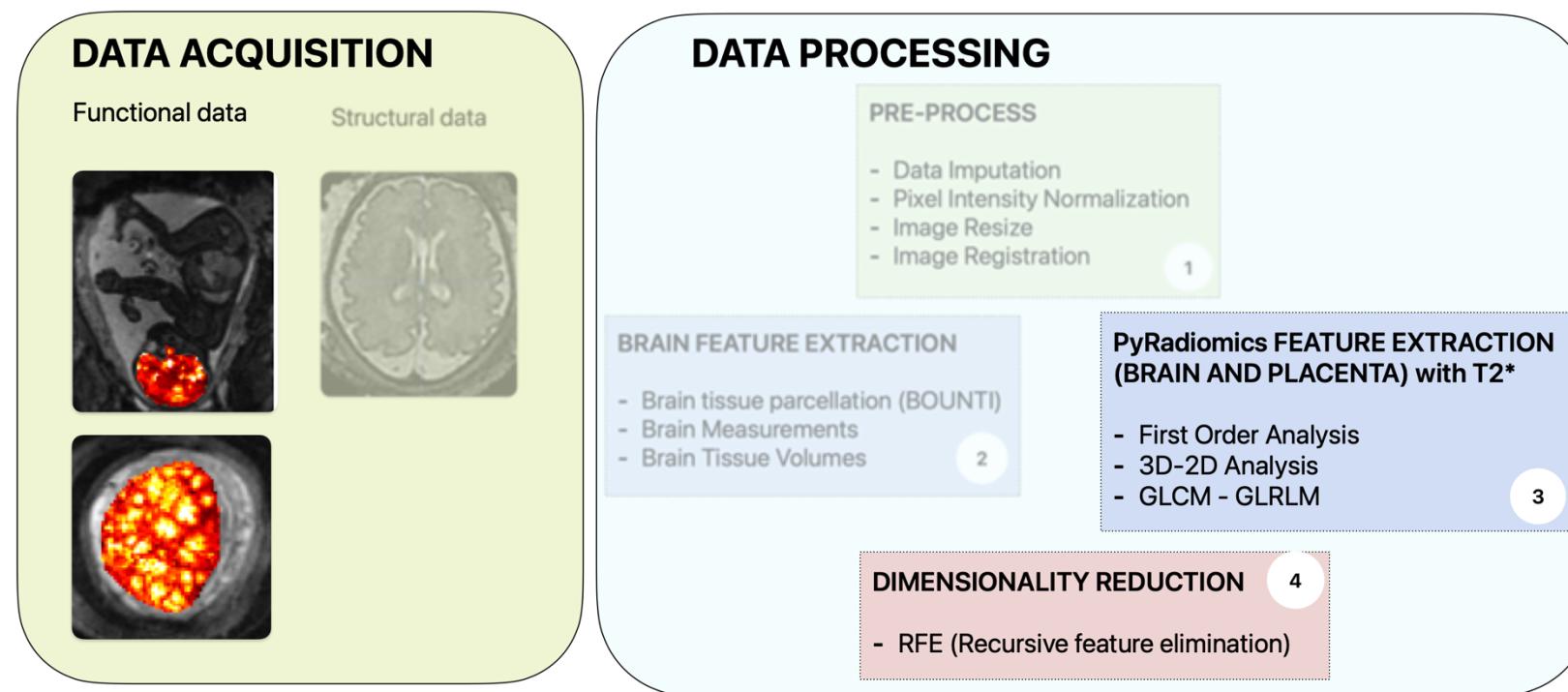
Table 3.2: Performance comparison of top VQ-VAE configurations (**embeddings + batch size + latent dim**)

Metric	256+10+16	256+10+64	256+50+32
Last MSE	0.060	0.058	0.054
Last VQ-VAE Loss	0.065	0.069	0.080
Last Reconstruction Loss	0.060	0.056	0.054
Last Loss	0.126	0.128	0.135
Average SSIM	0.222	0.201	0.254
DICE	0.276	0.275	0.282

Functional data T2* mapping

General Pipeline





Pre-eclampsia Model Output

Which organ?

Brain

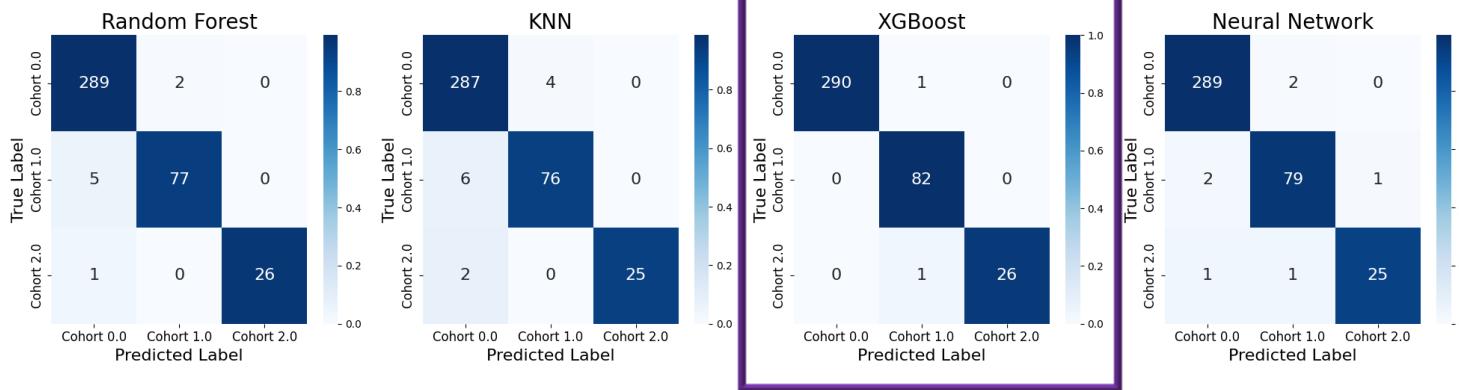


Table 3.4: Pre-eclampsia Probability Models Performance Comparison based on brain T2* mapping

Model	Accuracy	Precision	Recall	F1 Score
Random Forest	0.980	0.980	0.980	0.979
KNN	0.965	0.964	0.965	0.964
XGBoost	0.995	0.995	0.995	0.994
Neural Network	0.972	0.972	0.972	0.972

Placenta

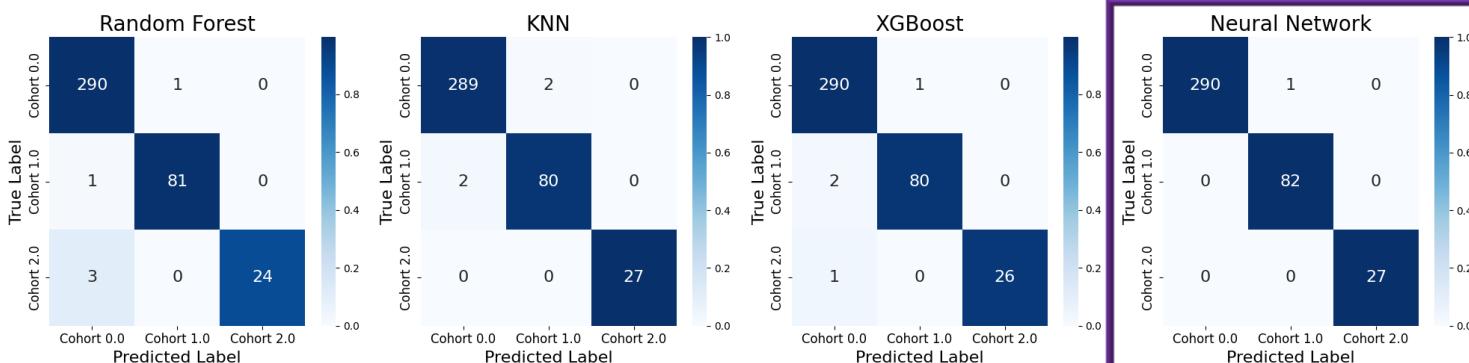
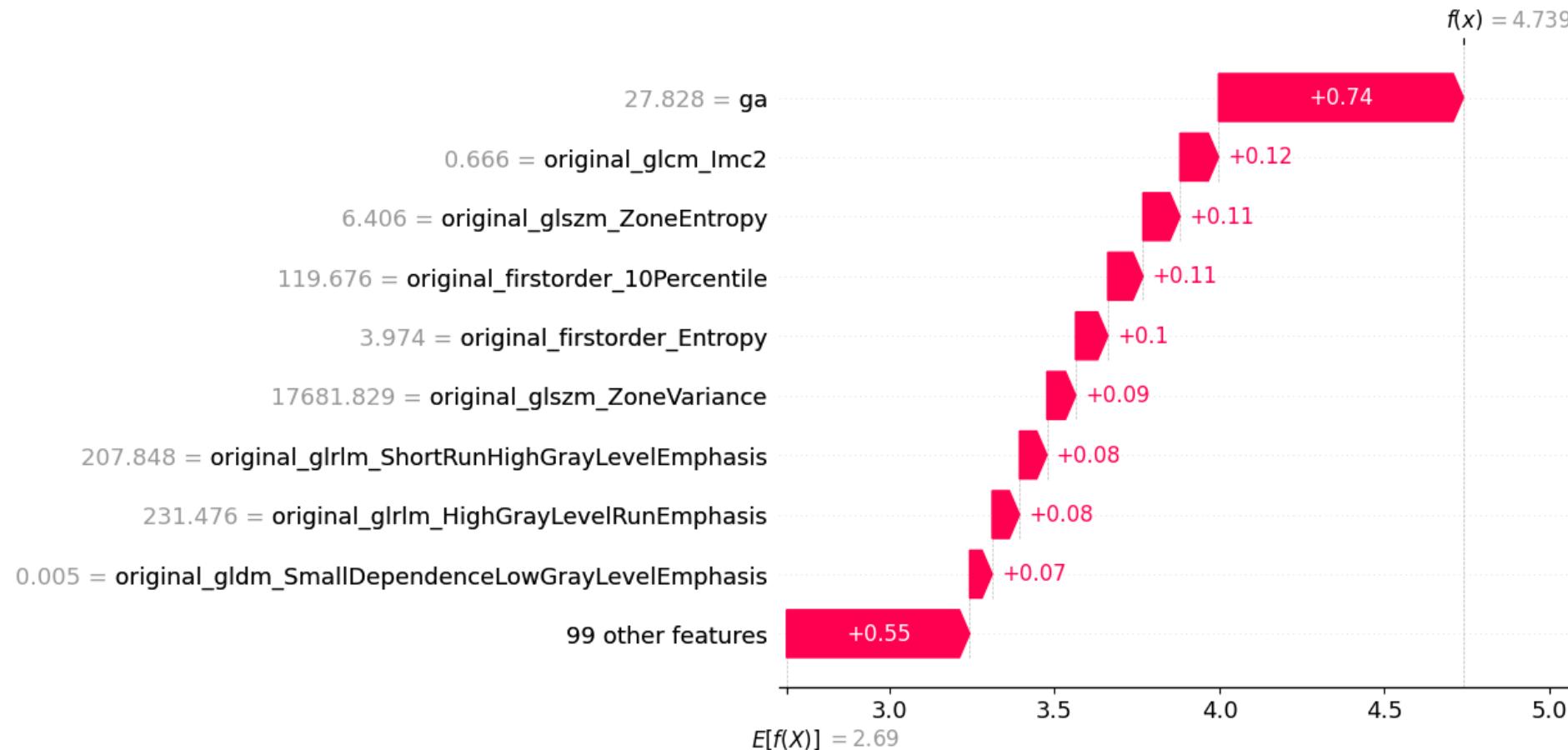


Table 3.5: Pre-eclampsia Probability Models Performance Comparison based on placental T2* mapping

Model	Accuracy	Precision	Recall	F1 Score
Random Forest	0.987	0.987	0.987	0.987
KNN	0.990	0.990	0.990	0.990
XGBoost	0.990	0.990	0.990	0.990
Neural Network	0.997	0.997	0.997	0.997

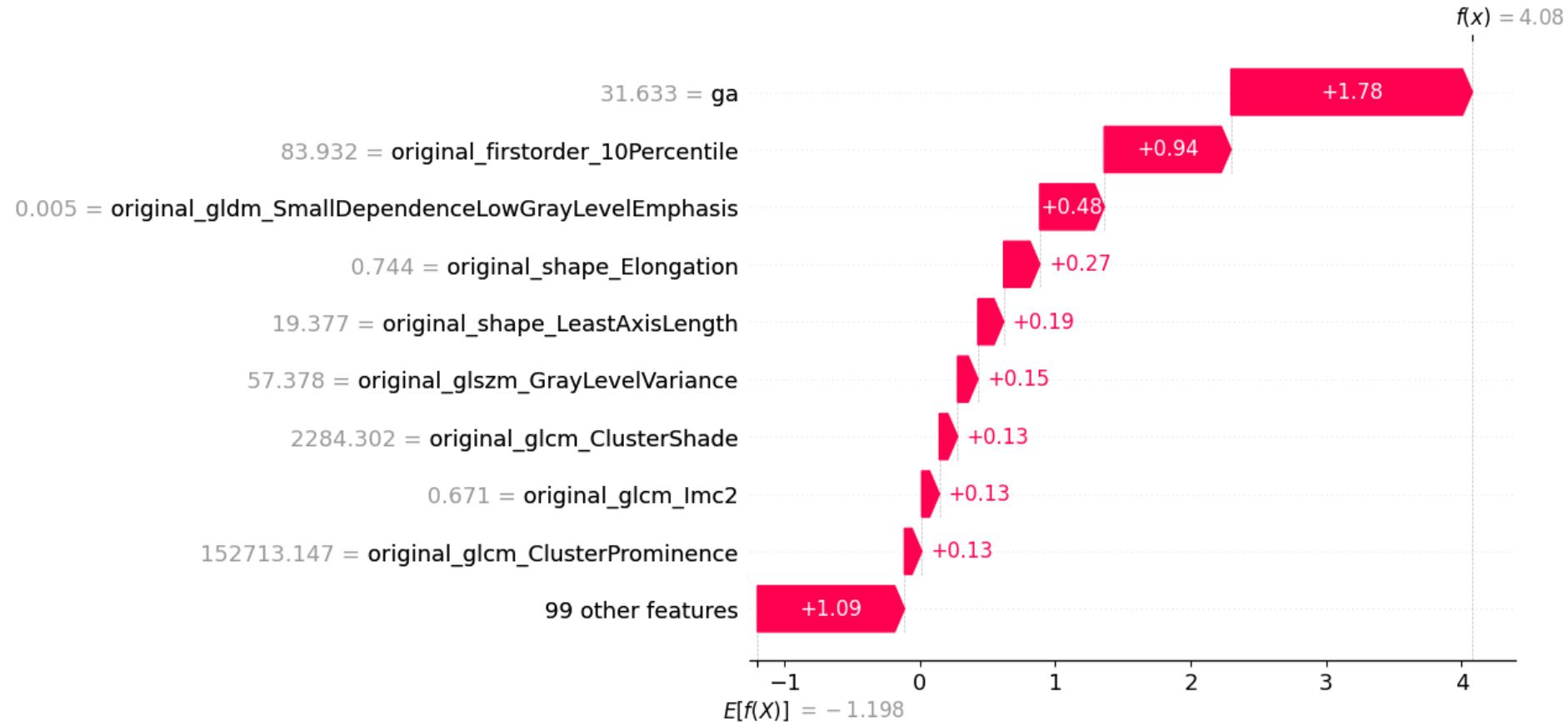
Bayesian Neural Network – Cohort 0 Negative cases

Which feature influence?



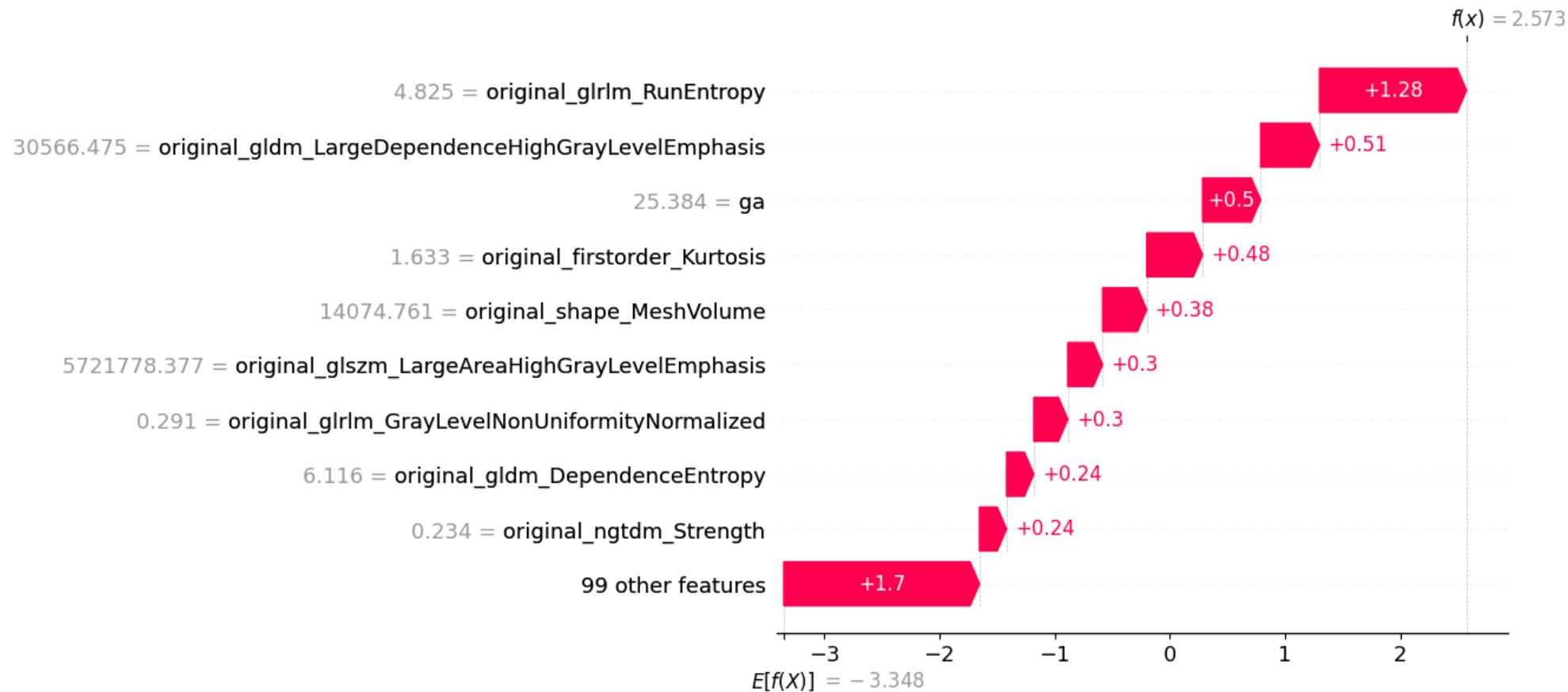
Bayesian Neural Network – Cohort 1 Positive cases

Which feature influence?



Bayesian Neural Network – Cohort 2 Chronic hypertension

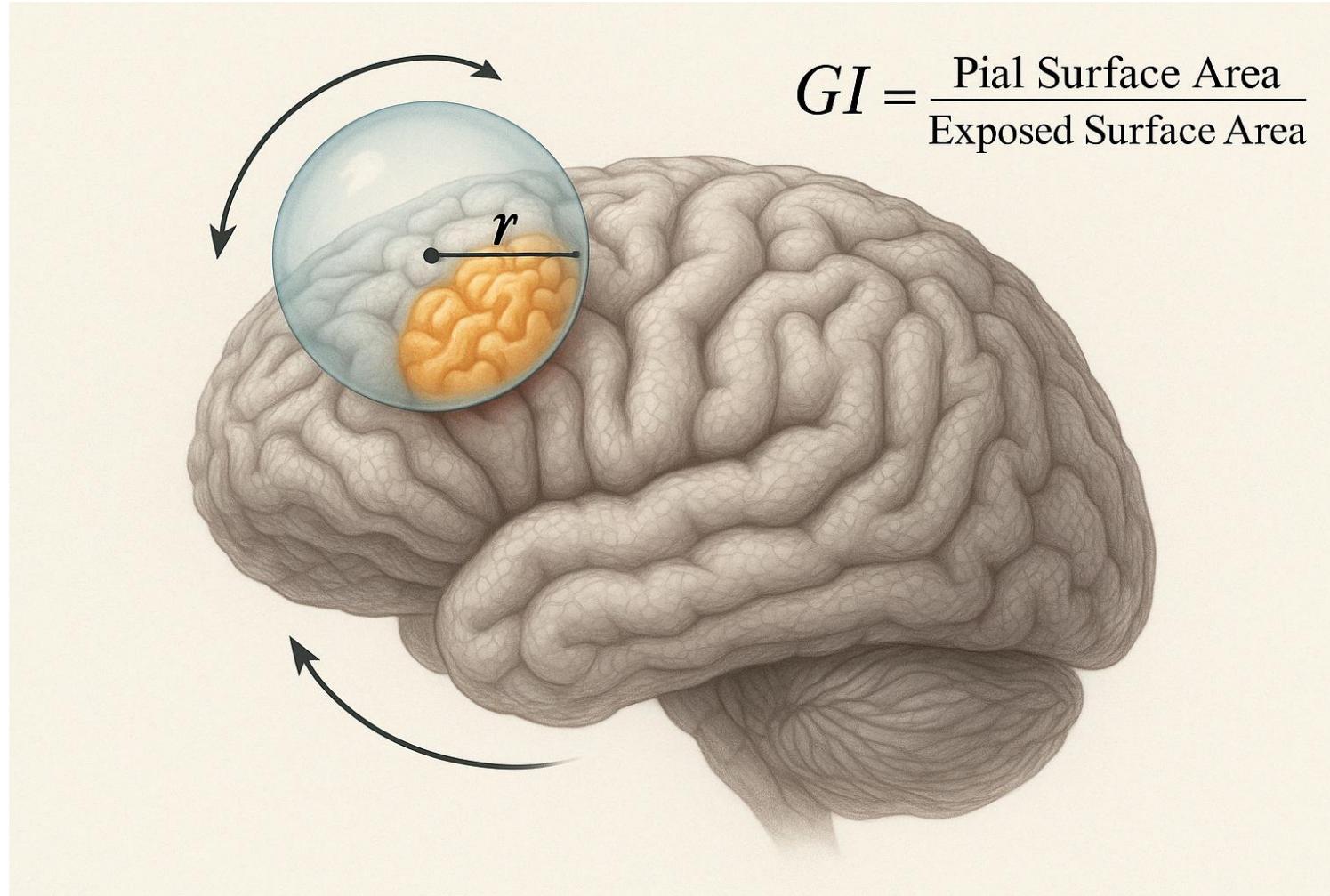
Which feature influence?



Gyrification Index Exploratory Experiment

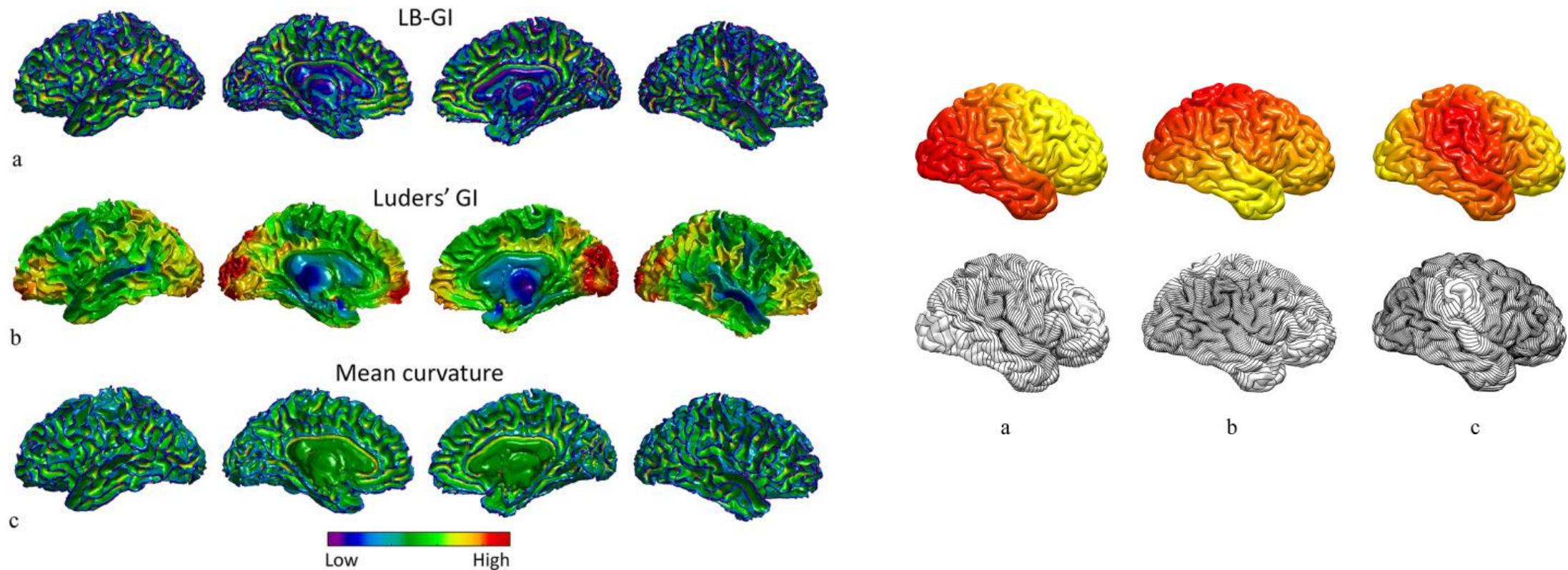
Idea...

$$GI = \frac{\text{Pial Surface Area}}{\text{Exposed Surface Area}}$$



Gyrification Index

Australia has done a good job ...



[1] Wang, Y., Xu, T., Kennedy, D. N., Zhang, J., Sadaghiani, S., Han, Y., & Liu, H. (2021). A gyrification analysis approach based on Laplace Beltrami eigenfunction level sets. *NeuroImage*, 229, 117758.
<https://doi.org/10.1016/j.neuroimage.2021.117758>

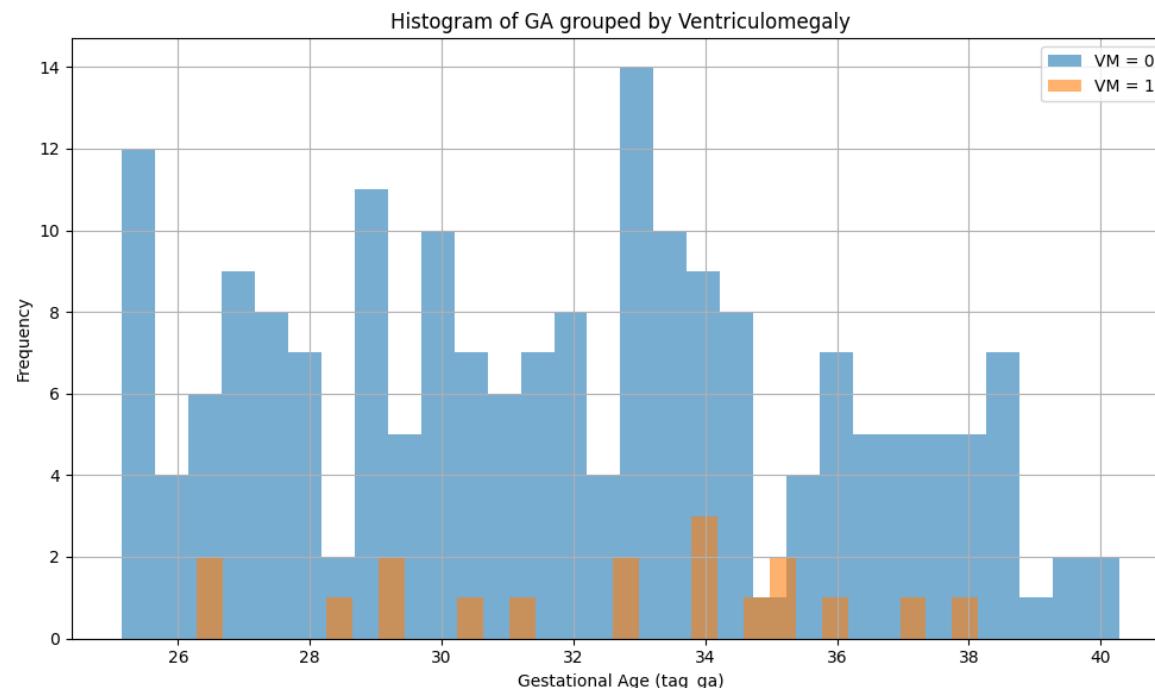
Conclusions

- GA prediction is feasible with **Linear Regression** and **Random Forest** models
- **XGBoost** is the top-performing model for ventriculomegaly classification
- **VQ-VAE** shows potential for anomaly detection but needs more training data and validation
- The **placenta** is a key region for pre-eclampsia prediction based on data and literature
- **Gyrification Index (GI)** is a marker of brain development linked to mental health conditions in research

-
- Models (Bayesian NN, XGBoost) run efficiently on CPUs
 - Modular “LEGO” framework for easy integration
 - Results affected by data imbalance
 - Output can be displayed as an interactive web report

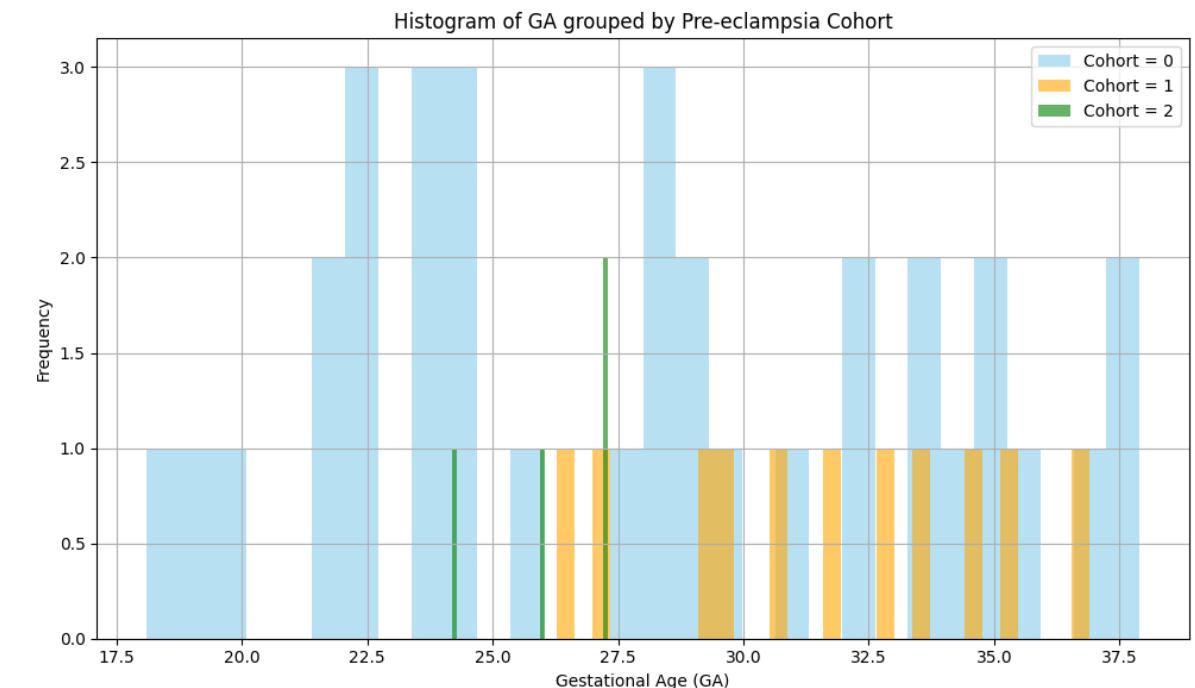
Future Directions

Include multi-center information



18 positive

53 negative



291 Cohort 0

82 Cohort 1

27 Cohort 2

Future directions

Clinical validation across sites

Gyrification Index (GI) refinement: Improve GI computation (e.g., University of Melbourne)

Expand to additional conditions: Extend the framework to include other prenatal conditions like fetal growth restriction (FGR), congenital heart defects (CHD), and cortical folding abnormalities

Include MRI contrasts: Incorporate Diffusion MRI (ADC), Intravoxel Incoherent Motion (IVIM), and T1-weighted imaging for richer tissue characterization

Teleradiology and LMIC applications: Adapt the tool for use in resource-limited settings with web-based interfaces (or EMR) and cloud support for remote fetal imaging assessment

Machine Learning are decision support mechanisms, not diagnostic tools!