



GESTATIONAL AGE-CONDITIONED ANOMALY DETECTION IN FETAL BRAIN MRI

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Introduction

- **Background:**
 - Fetal ventriculomegaly (VM) affects up to 2 in 1000 births and is associated with diverse neurodevelopmental impacts [1-3].
- **Deep Learning in Anomaly detection:**
 - Identifies unusual patterns that deviate from typical behaviors [4].
 - Anomaly detection in healthcare is particularly complicated due the context-specific nature of anomalies [4].
- **Importance of GA as a Covariate [5-8]:**
 - GA-based Analysis [5].
 - Importance of GA in ultrasound analysis.
 - Small for Gestational Age (SGA) Screening Model Development [6].
 - Prenatal MR Imaging for Brain Malformations [7].
 - Point-of-Care Ultrasound Improvements: GA estimation for better prenatal care [8].
 - Impact on Fetal Health Monitoring [5-8].
- **Other research [4]:**
 - Combining MRI with other imaging techniques for improved detection.
 - Auto-Encoders (AE), Variational Autoencoders (VAE) and Generative Adversarial Networks (GAN) for feature extraction.
 - Tailoring detection models to individual patient data.
 - Model Interpretation Strategies.

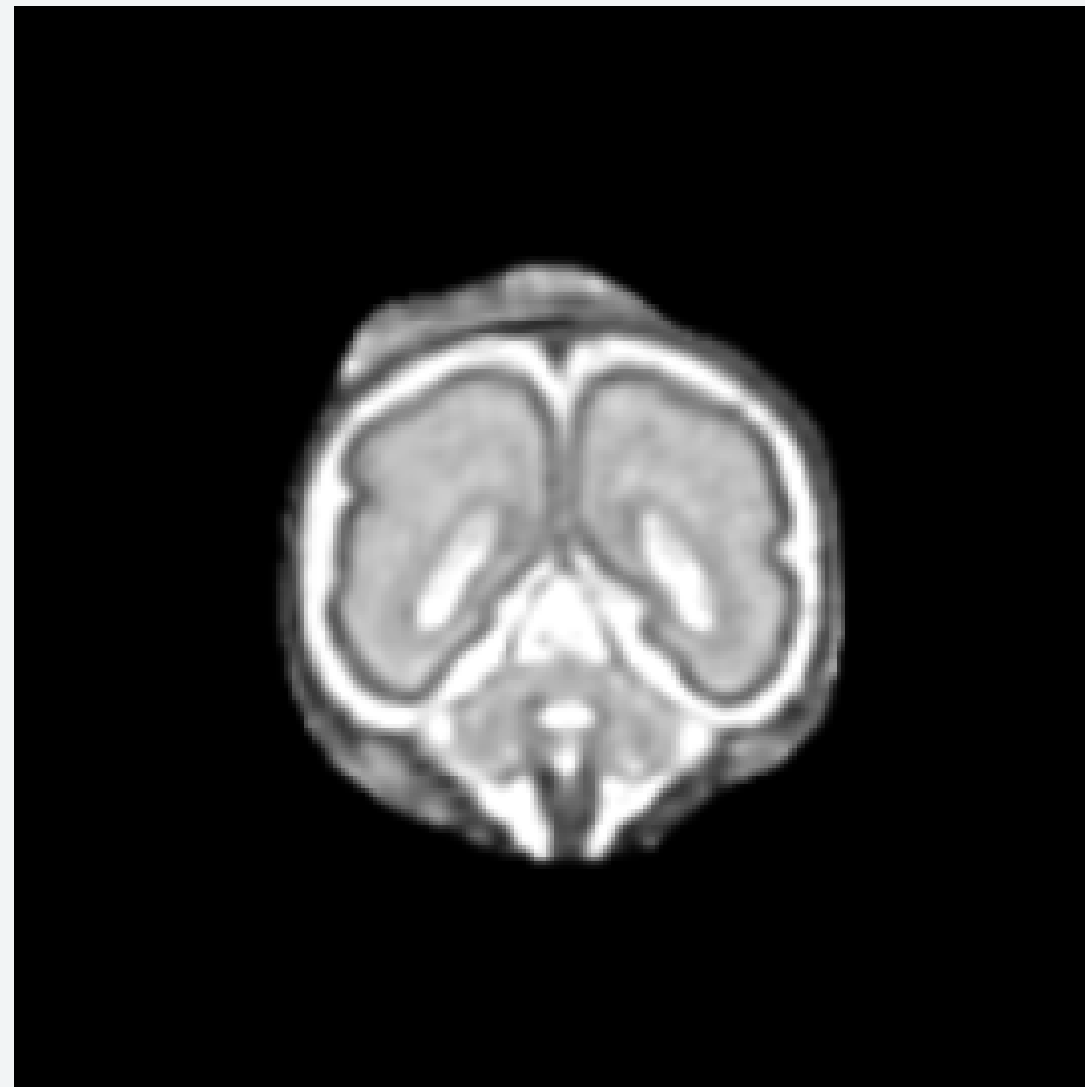
- [1] Pisapia et al., Child's Nerv Syst, 2017.
- [2] Chervenak et al., Lancet, 1984.
- [3] Weichert et al., Fetal Diagn Ther, 2010.
- [4] Fernando et al., ACM Comput Surv, 2021.
- [5] Alzubaidi et al., Diagnostics, 2022.
- [6] Gao et al., Journal of Clinical Medicine, 2023.
- [7] Conte et al., American Journal of Neuroradiology, 2016.
- [8] Maraci et al. Journal of Medical Imaging, 2020.



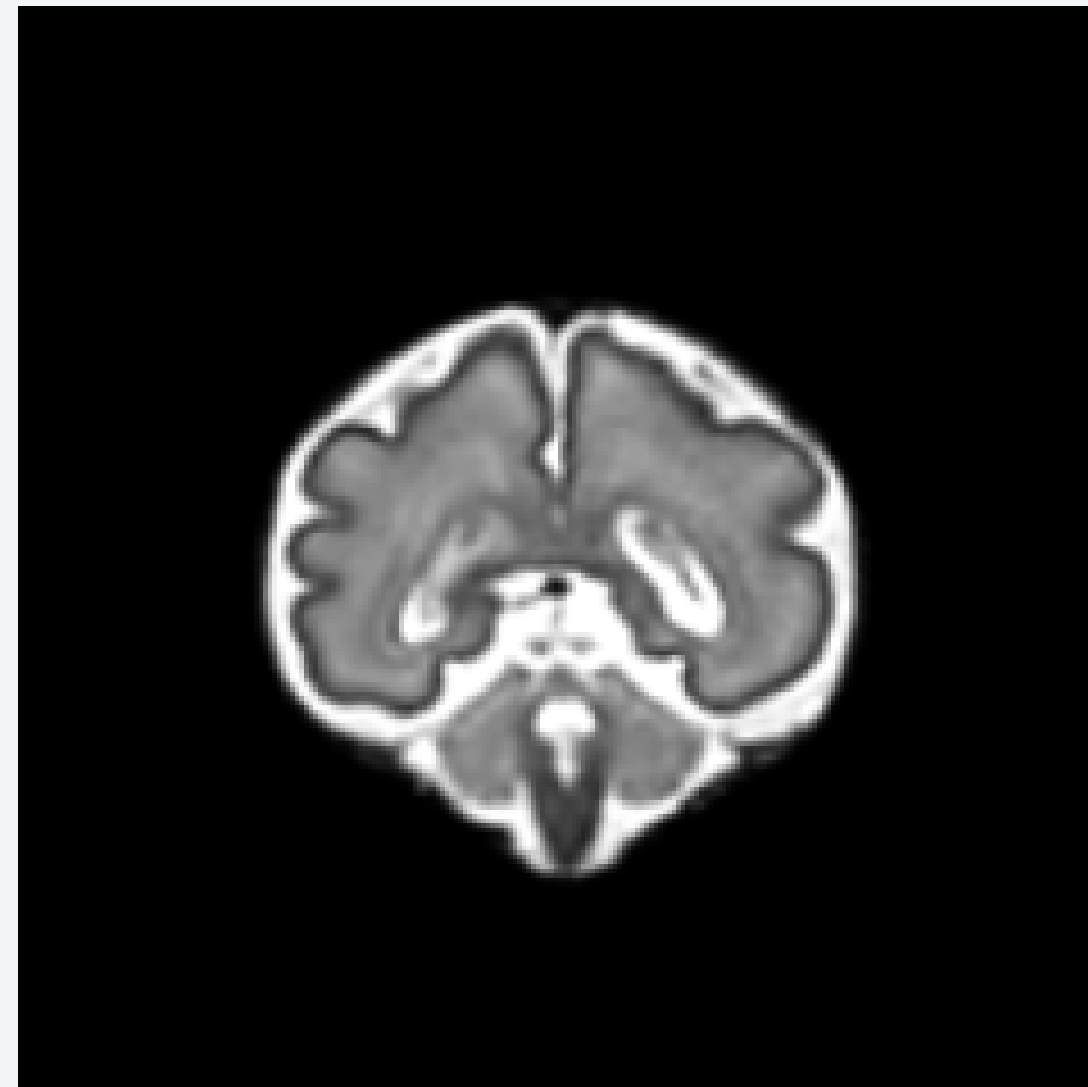
VM subject

Aim

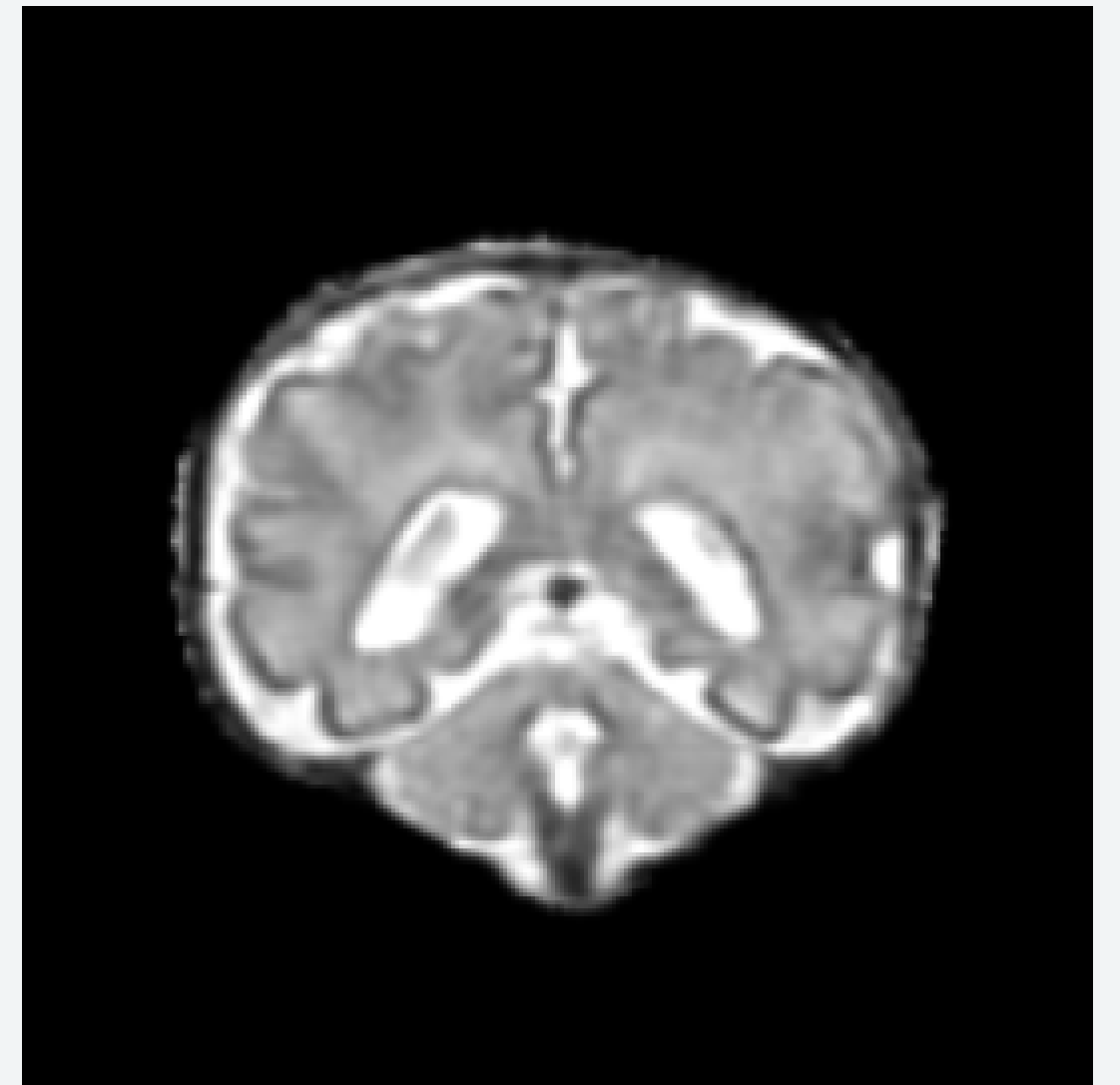
- **Objective:**
 - We aim to develop a Gestational Age (GA) conditioned VAE-based anomaly detection model for fetal MRI.
- **Anticipated Impact:**
 - Our research enhances fetal health monitoring through context-informed anomaly detection. This method aids in recognizing that certain structures or sizes may only be normal within specific developmental stages, which is crucial for the early and accurate identification of developmental anomalies.



GA 26.43



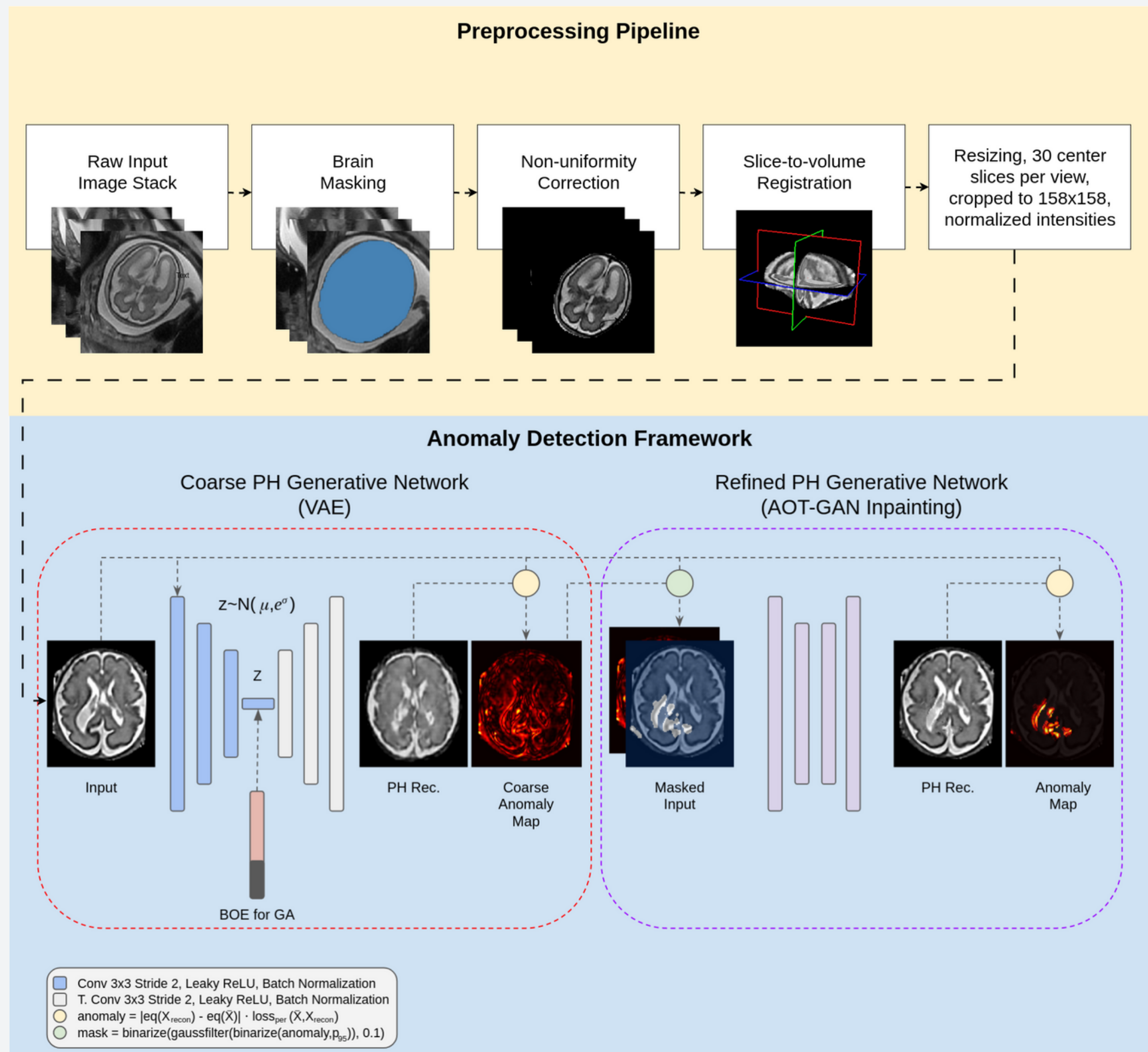
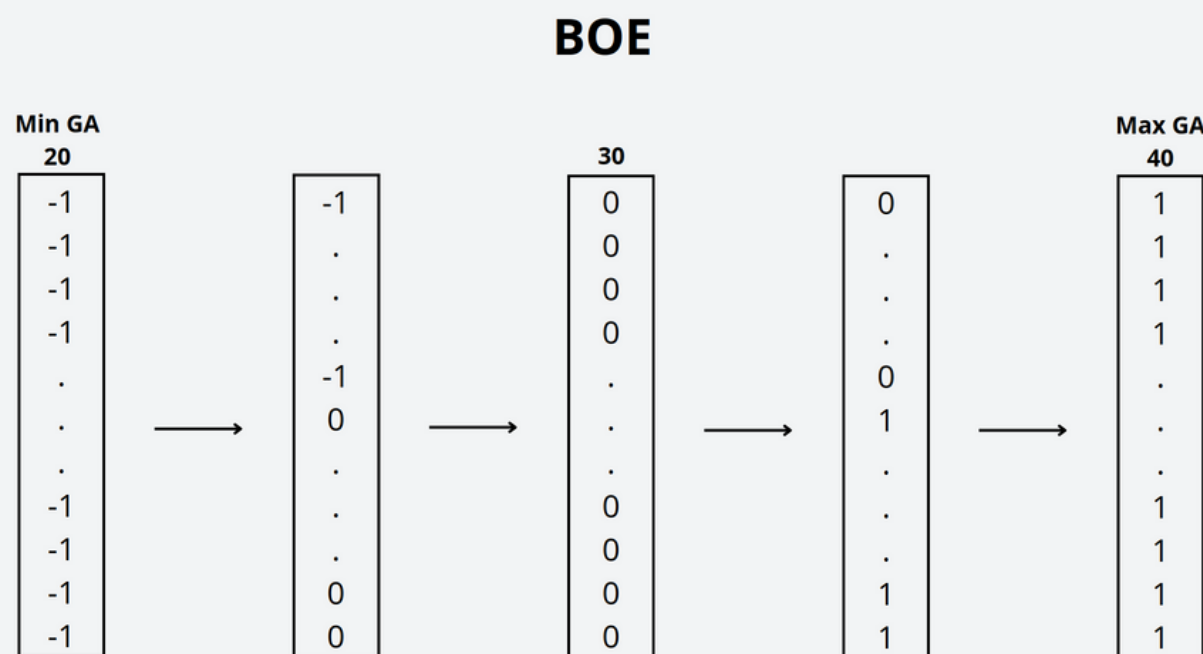
GA 28.86



GA 32.57

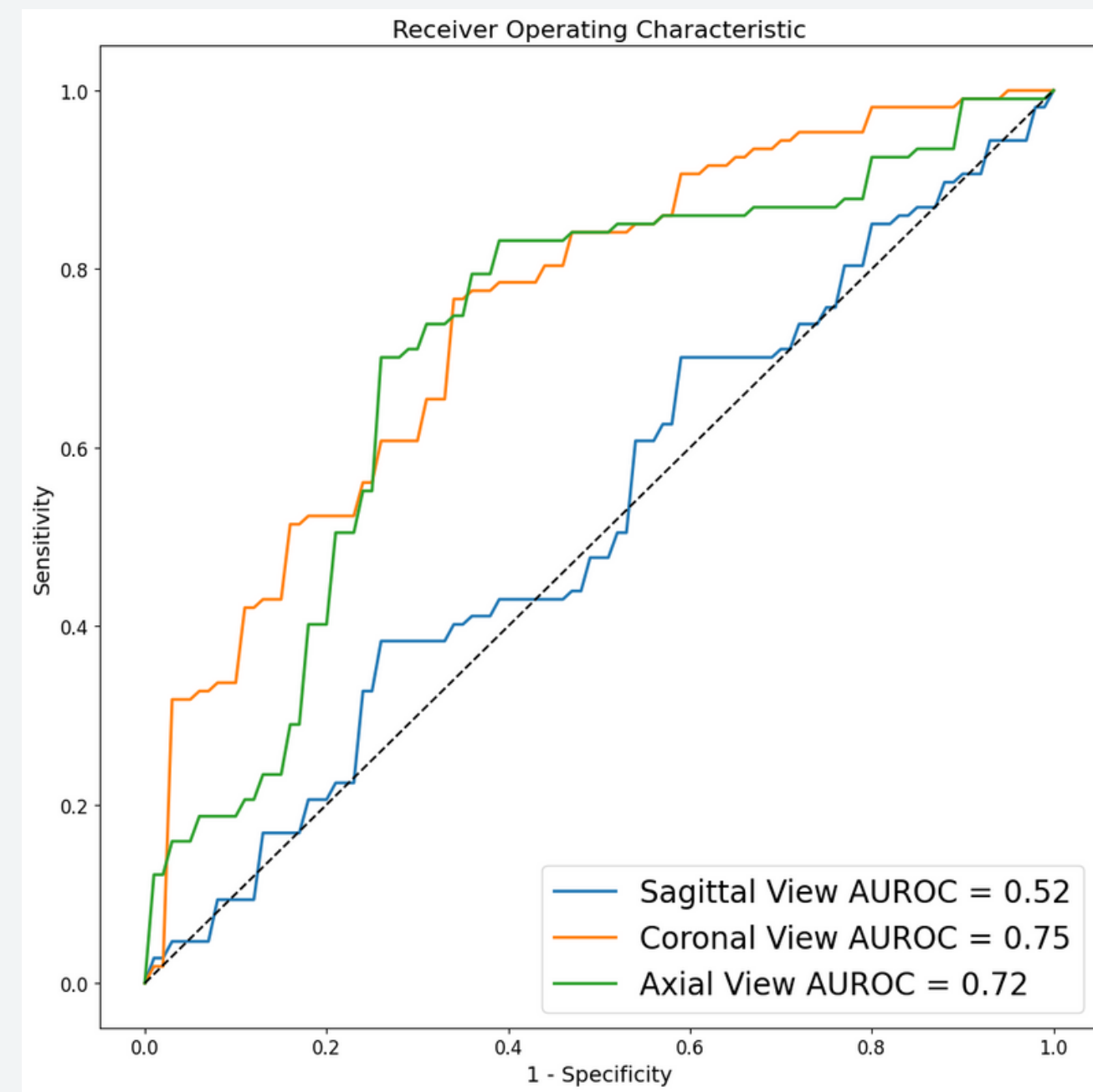
Method

- **Cohort Information:** 231 typically developing (TD) fetuses (GA: 30.27 ± 4.0).
 - **Training Group:** 192 TD fetuses.
 - **Testing Group:** 39 TD fetuses and 107 VM diagnosed fetuses (GA: 29.55 ± 3.72).
- **Statistical Method:** Employed the Mann-Whitney U test for comparing anomaly scores between TD and VM groups.
- **GA Encoding:** We proposed Bidirectional Ordinal Encoding (BOE) to include GA as a conditioning covariate.

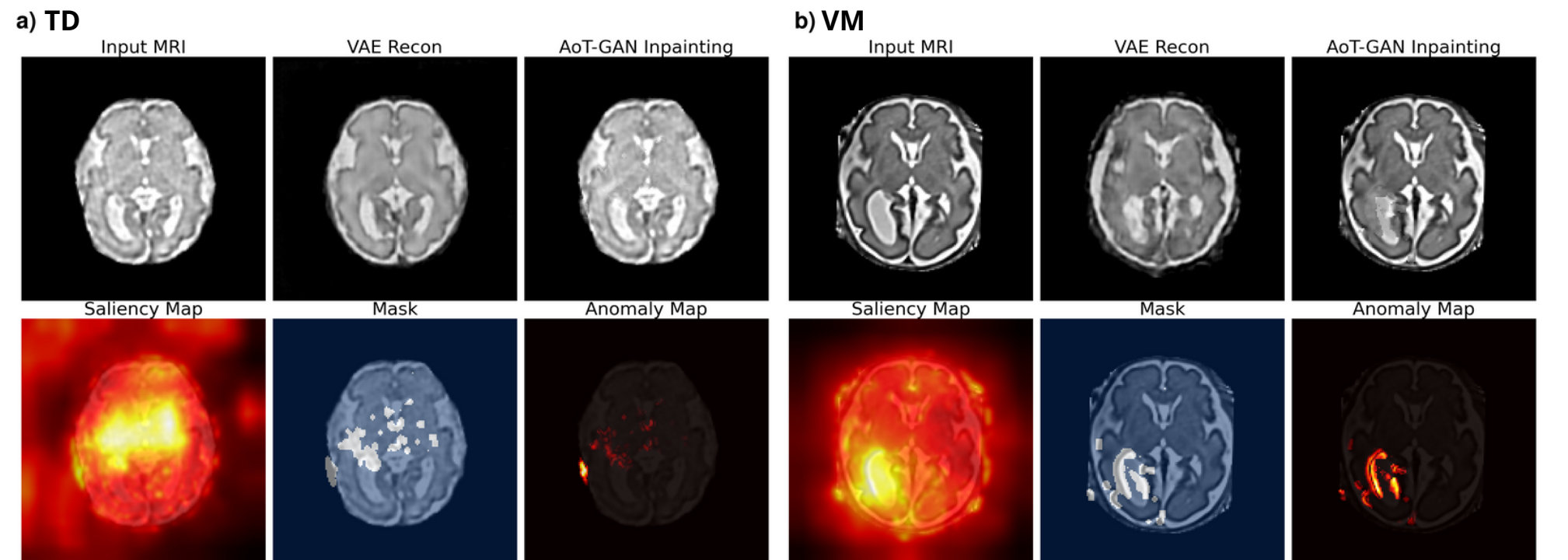


| View | Metric | TD | VM | P-Value |
|----------|---------------|---------------|---------------|-----------------|
| Sagittal | MSE | 0.0009±0.0036 | 0.0010±0.0036 | 0.6938 |
| | MAE | 0.0003±0.005 | 0.0003±0.0006 | 0.8770 |
| | Anomaly Score | 0.0010±0.0002 | 0.0011±0.0002 | 0.6808 |
| Coronal | MSE | 0.0008±0.0033 | 0.0012±0.0041 | <0.01 |
| | MAE | 0.0002±0.0005 | 0.0004±0.0006 | <0.01 |
| | Anomaly Score | 0.0008±0.0002 | 0.0010±0.0002 | <0.01 |
| Axial | MSE | 0.0009±0.0036 | 0.0012±0.0041 | <0.01 |
| | MAE | 0.0003±0.0006 | 0.0004±0.0006 | <0.01 |
| | Anomaly Score | 0.0010±0.0002 | 0.0011±0.0003 | <0.01 |

Mean Absolute Error (MAE), Mean Square Error (MSE) and Anomaly Score = $|eq(X_{recon}) - eq(X)| \cdot loss_{per}(X, X_{recon})$

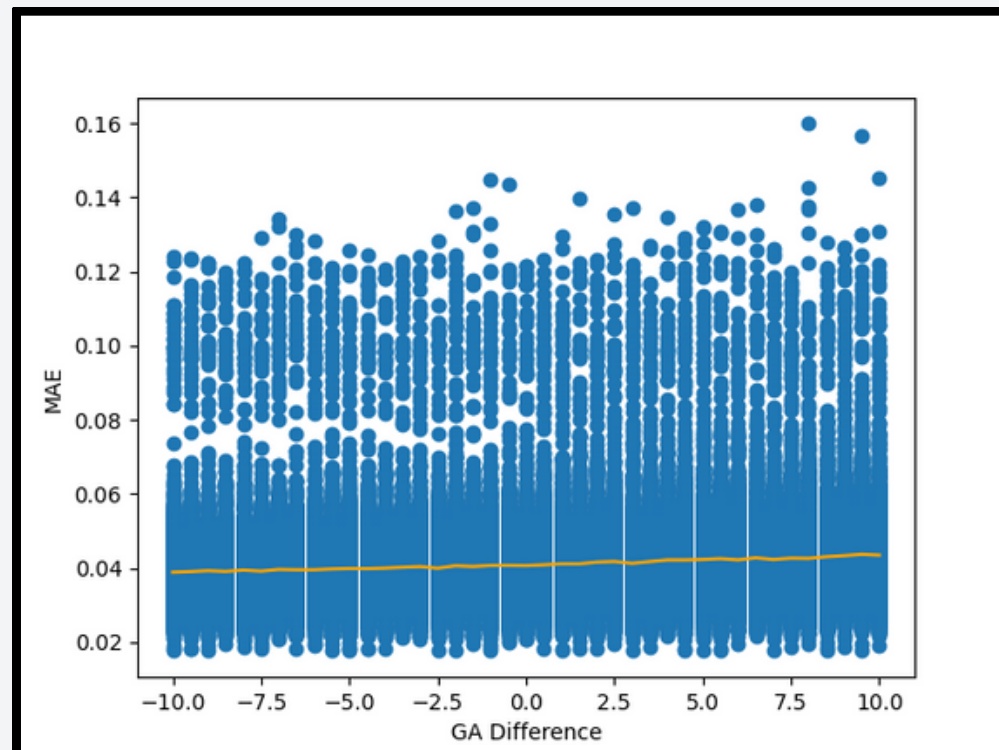


- Coronal and Axial views presented statistical significance ($p < 0.01$), while Sagittal didn't.
- Furthermore, ROC curve analysis demonstrates that the Coronal and Axial views are more reliable for detecting ventriculomegaly than the Sagittal view.
- The model showed clear differences in the anomaly map between TD and VM groups.

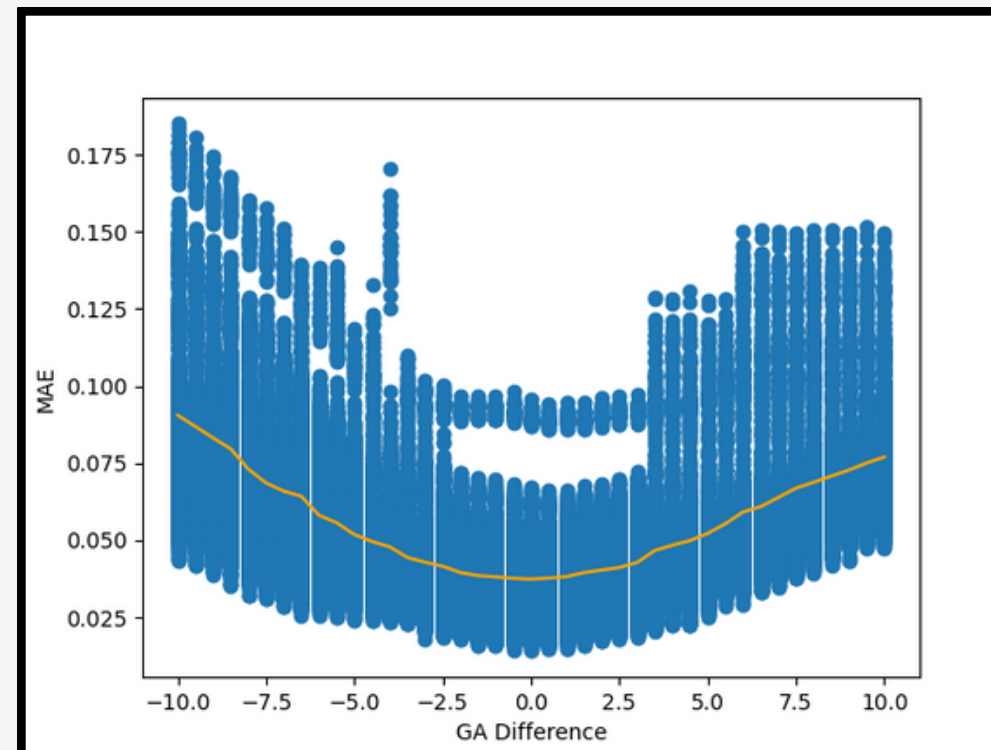


Discussion

- We developed a GA conditioned VAE-based anomaly detection model for fetal MRI that can identify VM.
- Current iterations of the model incorporate GA considerations within the VAE framework but lack integration of inpainting conditioning.
- Efforts to achieve clinically realistic outcomes from the model are ongoing and show promising progress.



Previous model effect of GA on MAE



New model effect of GA on MAE

- **GA Effect:**
 - Artificially altering the GA does affect the MAE, but more testing is still needed.

Next Steps

- **Adversarial VAE:**
 - Implement and train the VAE with an adversarial loss function.
- **Conditioned Inpainting GAN**
 - Implement and train the CGAN.