Gestational Age-Conditioned Anomaly Detection in Fetal Brain MRI

Guillermo Tafoya Milo[1,2], Sungmin You[2,3], Carlos S. Amador Izaguirre[2,4], Milton O. Candela Leal[2,5], Hyuk Jin Yun[2,3,6], P Ellen Grant[2,3,7], Kiho Im[2,3,6]

[1]*School of Engineering and Sciences, Computer Sciences Department, Tecnológico de Monterrey, Monterrey, NL, Mexico.*
[2]*Fetal-Neonatal Neuroimaging and Developmental Science Center, Boston Children's Hospital, Harvard Medical School, Boston, MA 02115, USA.*
[3]*Division of Newborn Medicine, Boston Children's Hospital, Harvard Medical School, Boston, MA 02115, USA.*
[4]*School of Engineering and Sciences, Mechatronics Department, Tecnológico de Monterrey, Guadalajara, JAL, Mexico.*
[5]*School of Engineering and Sciences, Mechatronics Department, Tecnológico de Monterrey, Monterrey, NL, Mexico.*
[6]*Department of Pediatrics, Harvard Medical School, Boston, MA, USA.*
[7]*Department of Radiology, Boston Children's Hospital, Harvard Medical School, Boston, MA 02115, USA.*

Background:

Fetal ventriculomegaly (VM) affects up to 2 in 1000 births and is associated with diverse neurodevelopmental impacts [1-3]. A significant challenge in healthcare anomaly detection is the variability and context-specific nature of anomalies, complicating differentiation between normal and problematic variations [4]. This has led to incorporating gestational age (GA) to improve diagnostic precision in cases like VM, where early detection in fetuses through MRI is vital [1,5] for analyzing causes, predicting developmental outcomes [6], and managing neurodevelopmental impairment risks.

Objective:

This study aims to develop a deep generative anomaly detection model in fetal brain MRI for the diagnosis of VM considering the GA.

Material and Methods:

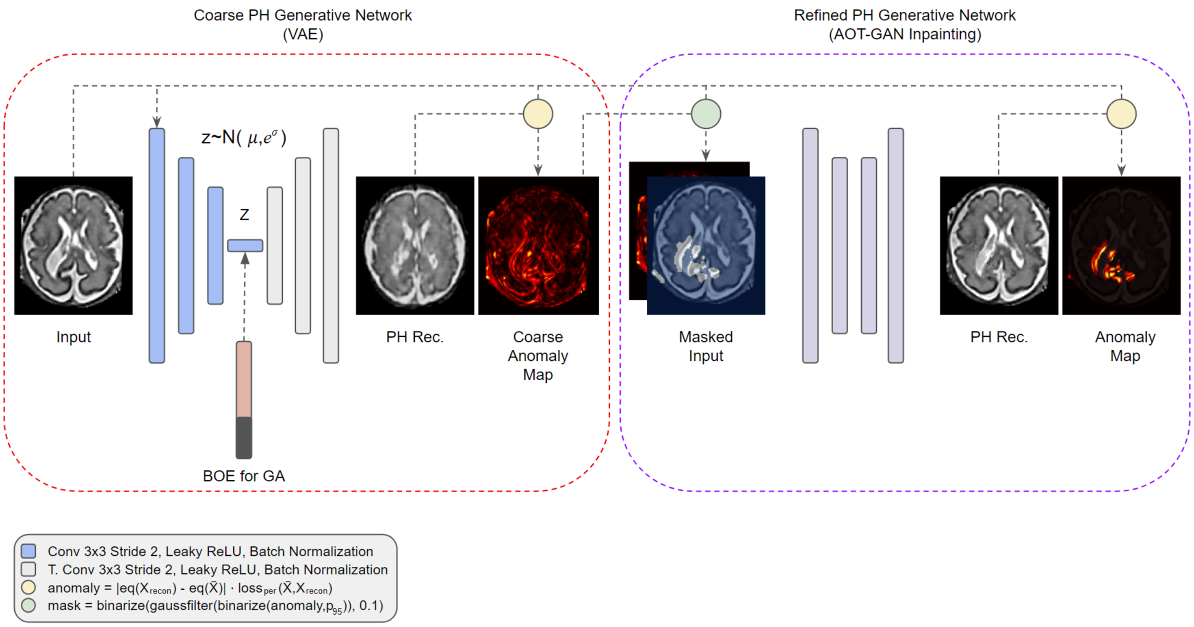
This study, approved by Boston Children's Hospital's Institutional Review Board, involved a cohort of typically developing (TD) fetuses (GA: 30.27±4.0), divided into two groups: 192 for training and 39 for testing. Included 119 fetuses (GA: 29.13±4.0) diagnosed with VM in the test set.

Using our fetal MRI pipeline [7], which encompasses brain masking, non-uniformity correction, and slice-to-volume registration [8], we prepared a dataset, resizing the MRI to native size to account for temporal variation along with GA as input for the model. We processed 30 center slices per view from each volume, cropped to 158x158, and normalized image intensities. [Figure 1] Our framework [9], consists of a VAE [10] for anomaly detection and AOT-GAN [11] for refinement. We proposed Bidirectional Ordinal Encoding (BOE) to include GA as a conditioning covariate [12]. A statistical analysis using the Mann–Whitney U test compared anomaly scores between TD and VM groups.

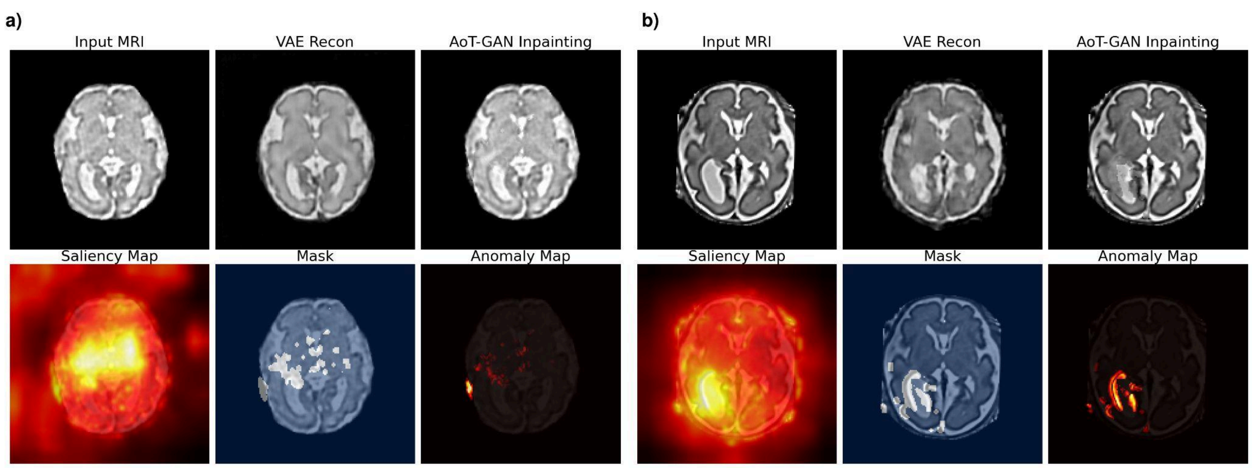
Results, Discussion, and/or Key Learning:

Our proposed model distinguished between TD and VM cases with an AUROC of 0.79 along anomaly scores showing statistical significance ($p<0.001$). The model showed clear differences in the anomaly map between TD [Figure 2, a] and VM [Figure 2, b] upon visual inspection.

Keywords: Fetal MRI, Ventriculomegaly, Unsupervised Deep Learning, Anomaly Detection, Neurodevelopmental Disorders



[Figure 1. Overview of the proposed anomaly detection framework for fetal brain MRI]



[Figure 2. Visualization of anomaly detection workflow: (a) Example of MRI in axial view from TD; (b) Example of MRI in axial view from VM. The sequence includes the original MRI input, the VAE reconstruction, the saliency map obtained from this initial reconstruct for the initial anomaly map and the mask, the mask for the AOT-GAN inpainting, the AOT-GAN inpainting for anomaly isolation, and final anomaly mapping for precise localization.]

References:

[1] J. M. Pisapia, S. Sinha, D. M. Zarnow, M. P. Johnson, and G. G. Heuer, "Fetal ventriculomegaly: diagnosis, treatment, and future directions," Child's Nervous System, vol. 33, pp. 1113-1123, 2017.

[2] F. Chervenak, L. Ment, M. Mcclure, C. Duncan, J. Hobbins, D. Scott, and R. Berkowitz, "Outcome of fetal ventriculomegaly," The Lancet, vol. 324, no. 8396, pp. 179-181, 1984.

[3] J. Weichert, D. Hartge, M. Krapp, U. Germer, U. Gembruch, and R. Axt-Fliedner, "Prevalence, characteristics and perinatal outcome of fetal ventriculomegaly in 29,000 pregnancies followed at a single institution," Fetal Diagnosis and Therapy, vol. 27, no. 3, pp. 142-148, 2010.

[4] T. Fernando, H. Gammulle, S. Denman, S. Sridharan, and C. Fookes, "Deep Learning for Medical Anomaly Detection – A Survey," ACM Computing Surveys, vol. 54, no. 7, Art. no. 141, Sep. 2021, pp. 1–37, doi: 10.1145/3464423.

[5] A. Pappas, I. Adams-Chapman, S. Shankaran, S. A. McDonald, B. J. Stoll, A. R. Laptook, W. A. Carlo, K. P. Van Meurs, S. R. Hintz, M. D. Carlson, J. E. Brumbaugh, M. C. Walsh, M. H. Wyckoff, A. Das, and R. D. Higgins; Eunice Kennedy Shriver National Institute of Child Health and Human Development Neonatal Research Network, "Neurodevelopmental and Behavioral Outcomes in Extremely Premature Neonates With Ventriculomegaly in the Absence of Periventricular-Intraventricular Hemorrhage," JAMA Pediatr, vol. 172, no. 1, pp. 32-42, Jan. 2018, doi: 10.1001/jamapediatrics.2017.3545.

[6] H. Cho, E. K. Kim, I. G. Song, J. S. Heo, S. H. Shin, and H. S. Kim, "Head growth during neonatal intensive care unit stay is related to the neurodevelopmental outcomes of preterm small for gestational age infants," Pediatr Neonatol, vol. 62, no. 6, pp. 606-611, Nov. 2021, doi: 10.1016/j.pedneo.2021.05.023.

[7] H. J. Yun, H. J. Lee, J. Y. Lee, T. Tarui, C. K. Rollins, C. M. Ortinau, H. A. Feldman, P. E. Grant, and K. Im, "Quantification of sulcal emergence timing and its variability in early fetal life: Hemispheric asymmetry and sex difference," NeuroImage, vol. 263, 2022, Article 119629, ISSN 1053-8119, https://doi.org/10.1016/j.neuroimage.2022.119629.

[8] M. Kuklisova-Murgasova, G. Quaghebeur, M. A. Rutherford, J. V. Hajnal, and J. A. Schnabel, "Reconstruction of fetal brain MRI with intensity matching and complete outlier removal," Med. Image Anal., vol. 16, no. 8, pp. 1550-1564, 2012, doi: 10.1016/j.media.2012.07.004.

[9] C. I. Bercea, B. Wiestler, D. Rueckert, and J. A. Schnabel, "Reversing the Abnormal: Pseudo-Healthy Generative Networks for Anomaly Detection," in H. Greenspan et al., Eds., Medical Image Computing and Computer Assisted Intervention – MICCAI 2023, Lecture Notes in Computer Science, vol. 14224, Springer, Cham, 2023, https://doi.org/10.1007/978-3-031-43904-9_29.

[10] D. P. Kingma and M. Welling, "Auto-encoding variational bayes," arXiv preprint arXiv:1312.6114, 2013.

[11] Y. Zeng, J. Fu, H. Chao, and B. Guo, "Aggregated Contextual Transformations for High-Resolution Image Inpainting," IEEE Transactions on Visualization and Computer Graphics, vol. 27, no. 6, pp. 3428-3441, 2021. DOI: 10.1109/TVCG.2021.3114788.

[12] T. Xia, A. Chartsias, and S. A. Tsaftaris for the Alzheimer's Disease Neuroimaging Initiative, "Consistent Brain Ageing Synthesis," in Medical Image Computing and Computer Assisted Intervention – MICCAI 2019, D. Shen et al., Eds., Lecture Notes in Computer Science, 2019.