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Automatic Placenta MRI Segmentation Across Gestational Stages Using nnUNet

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Introduction

Background:
- The placenta is a critical organ connecting the mother and fetus, essential for fetal development and maternal health.
- Abnormal placentas are associated with complications such as gestational hypertension and intrauterine growth restriction.
- Accurate placenta segmentation aids in pregnancy management and disease diagnosis.

Challenges:
- MRI data has limited resolution, blurred boundaries, and noise interference.
- Placental morphology varies across gestational stages, complicating model training.
- The uterine wall's complex structure makes manual annotation time-consuming and prone to errors.

Significance:
- Enhances segmentation efficiency, reducing manual annotation time.
- Improves annotation consistency by detecting errors and optimizing boundaries.
- Supports large-scale data analysis, providing technical assistance for medical research and clinical applications.

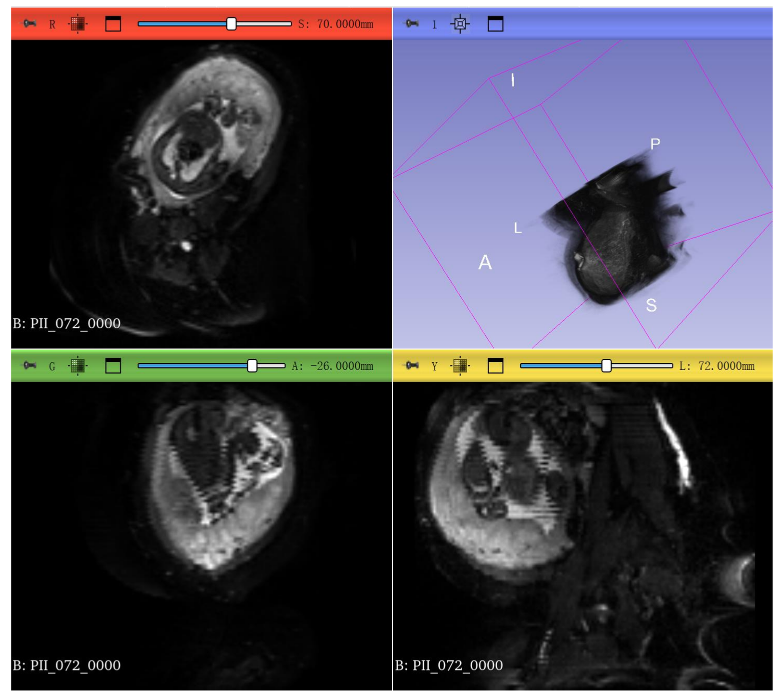

Figure 1 Patient 20's uterus MRI at gestational week 30, labeled as PII_072.nii.gz.

Objective

Target:
- Investigate the performance of nnUNet in placental MRI segmentation across different gestational stages, analyzing its adaptability to varying anatomical features.
- Compare segmentation results across stages to study the information relationships during placental development and explore potential medical applications.

Research Focus:
- Examine whether a segmentation model trained on one gestational stage can infer or predict results for other stages, reducing annotation efforts.
- Explore the feasibility of leveraging multi-stage segmentation data to optimize the performance for a specific stage, enhancing model flexibility and adaptability.

Methodology

Related Research and Rationale:
In recent years, deep learning has achieved significant progress in medical image segmentation, especially with the application of UNet and its variants [1][2].

However, these models often require extensive manual tuning of hyperparameters and architectural design. **nnUNet** offers an automated segmentation framework with adaptive data preprocessing, model configuration, and training strategy optimization, making it suitable for placental MRI segmentation tasks [3].

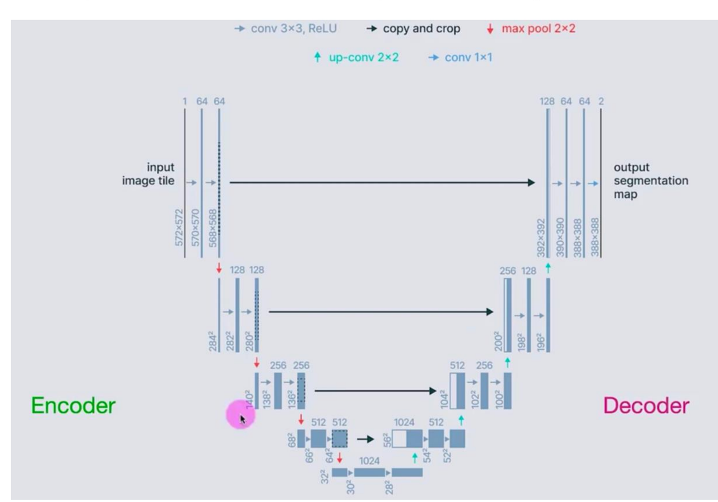

Figure 2. An example of the Unet architecture, primarily composed of encoder and decoder networks.

Overview of nnUNet:
- **Automated Pipeline:** nnUNet automates data preprocessing (e.g., normalization and resampling), model architecture selection (e.g., resolution adjustment and convolutional depth setting), and adaptive training schemes (e.g., learning rate optimization and loss function adjustment).
- **Optimization Features:** For placental data, nnUNet effectively handles resolution differences and noise in MRI, adapting to anatomical variations across different gestational stages.
- **Workflow Diagram:** As illustrated, nnUNet's automated process significantly reduces the need for manual intervention.

Performance Evaluation Metrics:
- $\text{Dice} = \frac{2\times|A\cap B|}{|A|+|B|}$
- $\text{IoU} = \frac{|A\cap B|}{|A\cup B|}$
- $\mathcal{L}_{\mathcal{D}c} = 1 - \frac{2\cdot|A\cap B|}{|A|+|B|+\varepsilon}, \varepsilon = 1\times 10^{-8}$

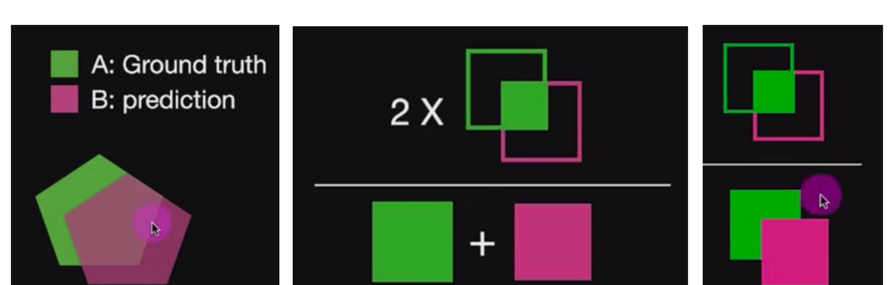

Figure 3 Model performance metrics for image segmentation, illustrated with Dice and IoU.

Experiment & Procedure

Experimental Data Description:
- Data Source: The dataset includes 132 placental MRI samples from 70 patients across 0-40 gestational weeks, annotated using 3D Slicer.
- Data Distribution: As shown in the Figure 4, the distribution of MRI samples across different gestational stages highlights the diversity of the data over time.
- Gestational Periods: These samples are grouped into three stages based on gestational periods, Early , Mid and Late Pregnancy.
- Each Uterus MRI Sample Size: The shape of each original uterus MRI, labels, and predicted segmentation is (128, 128, 115).
- Data Information: The dataset is provided by Yong Wang's Lab. For more details, contact: wangyong@wustl.edu.

Week-by-Week Statistics:

	Week	Number of seg.nii.gz Files
0	WK12	35
1	WK14	1
2	WK20	38
3	WK21	2
4	WK30	1
5	WK32	33
6	WK33	1
7	WK36	19
8	WK37	2
9	Total	132

Figure 4 Distribution of Uterus-Placenta MRI data across different gestational stages in the dataset.

Pregnancy Stage Statistics:

	Pregnancy Stage	Number of seg.nii.gz Files
0	Early Pregnancy (Week: 0-19)	36
1	Mid Pregnancy (Week: 20-30)	41
2	Late Pregnancy (Week 31-40)	55
3	Total	132

Figure 5 Classify into three types of Pregnancy based on gestational stages.

Uterus-Placenta Segmentation Metrics (nnUNet)

Model type with different periods	Model fitting ability on training set	Model generalization on validation set		Training set	Testing set	Model segmentation performance on testing set	
Training Data Composition	train_loss	val_loss	Pseudo dice	**Placenta Traing Periods**	**Placenta Test Periods**	Dice	IoU
Combined/Cross-stages	-0.9215	-0.7742	0.8534	0-40 Week (105)	0-40 Week Randomly (27)	0.8031	0.6839
Single-stage	-0.9231	-0.5922	0.6123	0–19 Week Placenta (36)	20-30 Week Placenta (41)	0.6913	0.5512
					31-40 Week Placenta (55)	0.1189	0.0732
	-0.9515	-0.8661	0.8805	20–30 Week Placenta (41)	0-19 Week Placenta (36)	0.564	0.4203
					31-40 Week Placenta (55)	0.6166	0.5072
	-0.9542	-0.8226	0.8637	31–40 Week Placenta (55)	0-19 Week Placenta (36)	0.1601	0.1034
					20-30 Week Placenta (41)	0.7568	0.6289
Mixed-stage	-0.9401	-0.8355	0.8626	20–30 (41) + 31-40 Week Placenta (55) -> 86	0–19 Week Placenta (36)	0.452	0.3268
	-0.9097	-0.8041	0.8556	0–19 (36) + 31-40 Week Placenta (55) -> 91	20–30 Week Placenta (41)	0.8386	0.7267
	-0.9235	-0.7414	0.8079	0–19 (36) + 20-30 Week Placenta (41) -> 77	31–40 Week Placenta (55)	0.5805	0.4768

Figure 7 Experimental results and performance of nnUNet trained on different gestational stage data, based on 132 MRI datasets.

Preview for Experimental Settings and Hyperparameters:
- Key Settings: 3D full-resolution mode, 5-fold cross-validation, 350 training epochs.
- GitHub Link: https://github.com/WenqingZhang123/Automatic-Placenta-Segmentation-on-MRI-Through-Gestational-Stages

Data Processing and Experimental Procedure:

1. Data Preprocessing:
- Convert MRI data to a standardized format and perform normalization and resampling to fit the nnUNet automated workflow.
- Split the dataset into training, validation, and testing sets using a 5-fold cross validation approach.

2. Model Training:
- Train the model using nnUNet v2 with a 3D full-resolution mode for 350 epochs.
- Hyperparameters include learning rate adjustment strategies and optimization based on the Dice loss function.

3. Model Inference and Evaluation:
- Perform inference on the test set using the trained model to generate segmentation results.
- Evaluate segmentation performance using Dice and IoU as quantitative metrics.

4. Experimental Workflow Diagram:
- The workflow includes data preprocessing, model training, inference, and evaluation, simplified as a graphical representation.

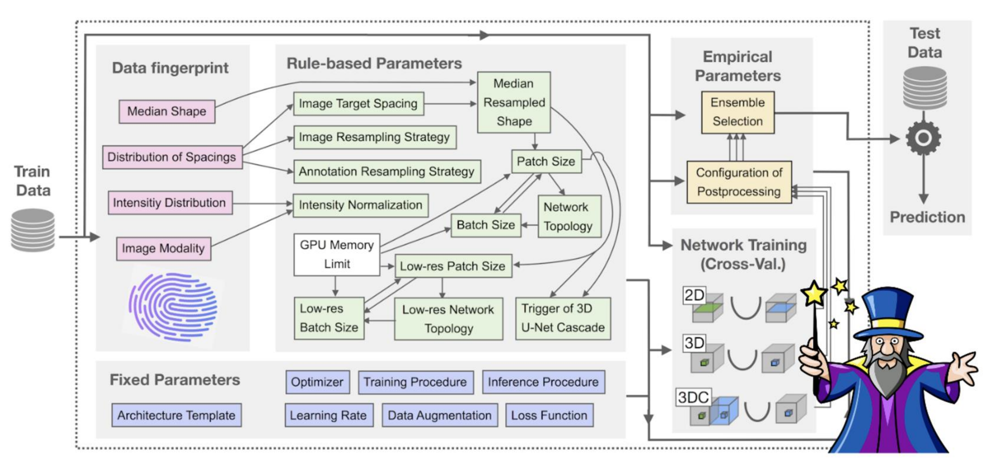

Figure 6 Complete nnUNet pipeline: preprocessing, training, prediction, and evaluation [3].

Results & Analysis

Introduction to Experimental Results of Figure 7:
This experiment applied nnUNet to placental MRI data across three gestational stages: early (0-19 weeks), mid (20-30 weeks), and late (31-40 weeks). The design consists of three groups:

- All-Stage Training Group: Training on combined data from all gestational stages and testing on a random test set.
- Single-Stage Training Group: Training on a single gestational stage and testing on other stages.
- Two-Stage Combined Training Group: Training on two gestational stages and testing on the remaining stage.

Performance is measured using Dice and IoU, demonstrating segmentation effectiveness across different training and testing combinations.

Combined gestational stages:
- Results:
  - In single-stage training, the model achieved strong fitting performance (train loss < -0.92) and pseudo dice above 82% on validation sets. For combined training across all stages, the test Dice reached 80.31%, demonstrating robustness in segmenting placentas across gestational stages.
- Analysis: nnUNet effectively captures stage-specific placental features in single-stage training and is highly adaptable for generalized segmentation tasks across multiple stages.

Mixed-stage training on other gestational stages:
- Results:
  - Combining mid and late stages for early-stage prediction yielded a Dice of 45.2%, lower than using mid-stage alone, suggesting that late-stage features interfered with early-stage learning.
  - Combining early and late stages for mid-stage prediction achieved a Dice of 83.86%, comparable to mid-stage self-training, indicating that early and late stages provided sufficient complementary information.
  - Combining early and mid stages for late-stage prediction achieved a Dice of 58.05%, slightly better than mid-stage alone, as mid-stage includes abundant late-stage features supplemented by some early-stage information.
- Analysis: Increasing the proportion of early and late-stage data, especially early-stage data, could improve segmentation performance across different gestational stages.

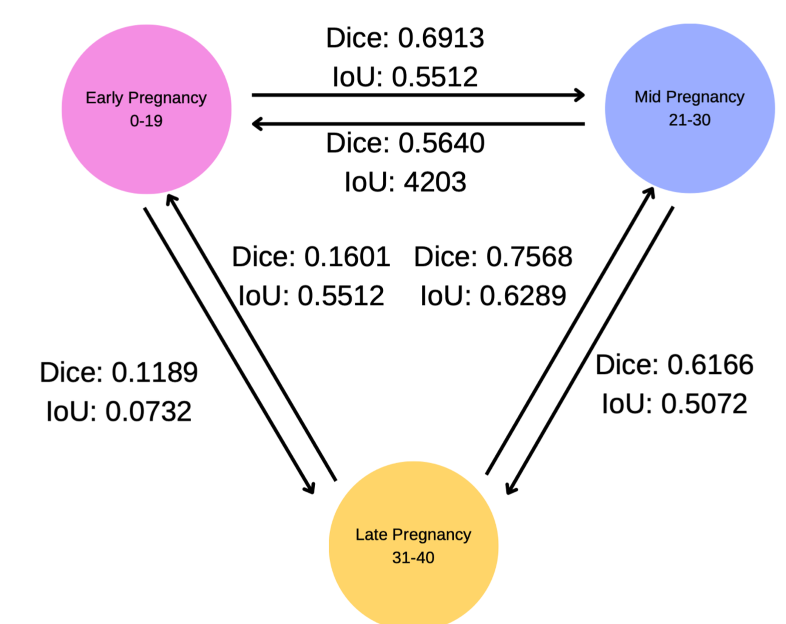

Figure 8 Performance of different single-stage models trained to predict segmentation for other periods.

Single-stage training on other gestational stages:
- Results:
  - The early-stage model achieved a Dice of 69.13% for mid-stage but only 11.89% for late-stage, indicating significant feature disparities between early and late stages.
  - The mid-stage model achieved Dice values of 56.4% and 61.66% for early and late stages, reflecting its transitional characteristics with features resembling both early and late stages.
  - The late-stage model performed well for mid-stage (Dice = 75.68%) but poorly for early-stage (Dice = 16.01%).
- Analysis: The transitional characteristics of mid-stage placentas make them suitable as a bridge for cross-stage segmentation, as mid-stage features include more late-stage-specific information. In contrast, the distinct differences between early and late stages require specialized optimization.

Conclusion & Future

Conclusion :
- nnUNet demonstrates excellent segmentation performance on placental images across individual and combined gestational stages. Specialized models for specific stages outperform general models, indicating better feature learning for stage-specific characteristics.
- Mid-stage placentas act as a transition phase between early and late stages, incorporating features from both but leaning more toward late-stage characteristics. Early and late stages exhibit significant differences, showing distinct independence.
- In mixed-stage training, increasing the proportion of early and late-stage data, especially early-stage data, can improve model performance and outperform evenly distributed data strategies.

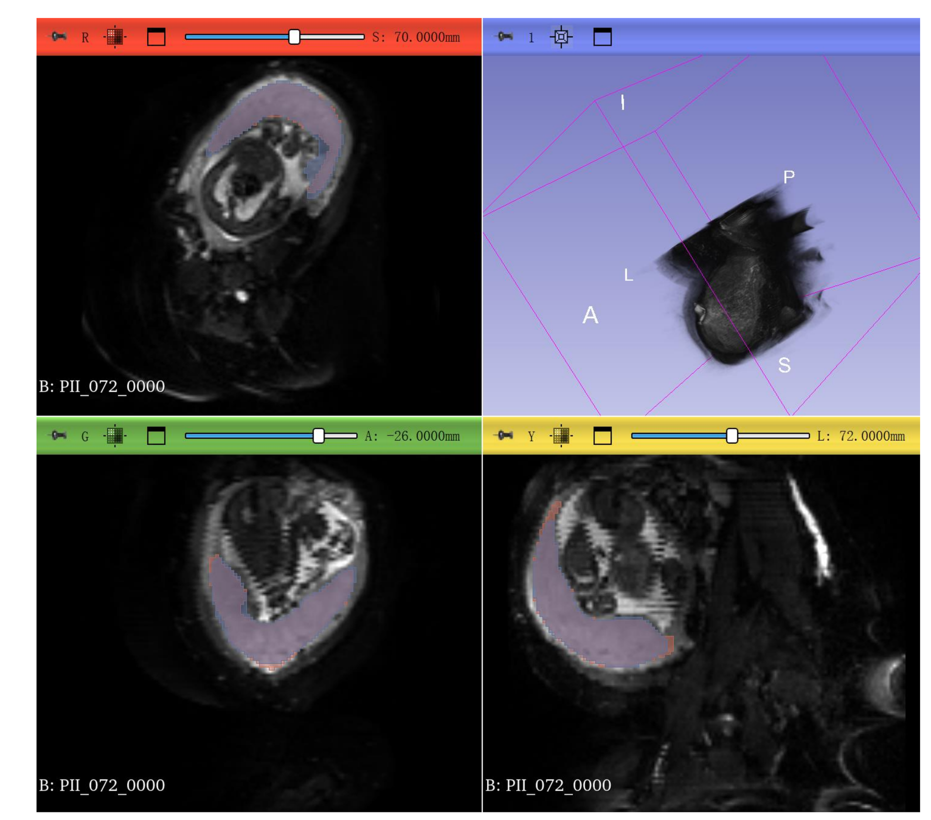

Figure 9 In Figure 1, the model achieves **Dice 93.23% and IoU 87.31%** on the Uterus-Placenta MRI with the code PII_072.nii.gz, where the **original** is shown in **Grey & White, ground truth in Red,** and **prediction in Blue.**

Future Work :
- Further optimize mixed-stage training strategies by balancing weights to enhance learning of early and late-stage features.
- Explore multi-modal segmentation approaches (e.g., combining MRI and ultrasound) to improve model generalizability.
- Expand the dataset with more samples across gestational stages, especially underrepresented phases, to improve model robustness and applicability.

Live Demo

Figure 10 Scan the QR code to view **the 3D MRI Comparison** with original, ground truth, and predicted labels on GitHub.

Reference:

[1]. Ronneberger, O., Fischer, P., & Brox, T. (2015). U-net: Convolutional networks for biomedical image segmentation. In Medical image computing and computer-assisted intervention–MICCAI 2015: 18th international conference, Munich, Germany, October 5-9, 2015, proceedings, part III 18 (pp. 234-241). Springer International Publishing.

[2]. Çiçek, Ö., Abdulkadir, A., Lienkamp, S. S., Brox, T., & Ronneberger, O. (2016). 3D U-Net: learning dense volumetric segmentation from sparse annotation. In Medical Image Computing and Computer-Assisted Intervention–MICCAI 2016: 19th International Conference, Athens, Greece, October 17-21, 2016, Proceedings, Part II 19 (pp. 424-432). Springer International Publishing.

[3]. Isensee, F., Jaeger, P. F., Kohl, S. A., Petersen, J., & Maier-Hein, K. H. (2021). nnU-Net: a self-configuring method for deep learning-based biomedical image segmentation. Nature methods, 18(2), 203-211.