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FeTA 2024 Challenge

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Introduction

Objective - Automated Fetal Brain MRI Segmentation and Biometry Prediction Using 3D U-Net Models in FeTA 2024

- **Segmentation Model:** Implemented a 3D U-Net with five levels of depth, residual connections, and specific configurations using the MONAI framework.
- **Biometry Model:** Designed a custom BiometryModel combining a 3D U-Net for feature extraction with a fully connected regression head to predict biometry values.

Task – 1 Segmentation Model

Architecture Details:

- **3D U-Net** implemented using the **MONAI framework**.
- **Input:** Single-channel 3D MRI volumes resized to **128×128×128** voxels.
- **Output:** 57-channel output matching unique label classes.
- **Network Configuration:**
  - **Depth Levels:** 5 with residual connections.
  - **Channels per Layer:** (16, 32, 64, 128, 256).
  - **Kernel Size:** 3×3×3.
- **Initialization:** Kaiming Normal for weights; biases initialized to zero.

Training Details:

- **Loss Function:** Dice Loss.
- **Optimizer:** Adam optimizer with learning rate **1e-4**.
- **Batch Size:** 1 (due to computational constraints).
- **Epochs:** 1500.
- **Training Time:** Approximately **10 hours** on an **RTX 4090 GPU**.

Task – 1 Segmentation Preprocessing and Augmentation

Preprocessing

- **Normalization:** Intensity scaling.
- **Resampling:** Uniform voxel spacing of **1.5×1.5×1.5 mm**.
- **Reorientation:** Standardized to RAS coordinate system.
- **Cropping and Resizing:** Cropped

Data Augmentation:

- **Random Flips:** 50% probability along one axis.
- **Random Rotations:** 90-degree rotations with 50% probability.
- **Intensity Shifts:** Random shifts with an offset of 0.1, 50% probability.

Task – 2 Biometry Model

Architecture Details:

- **Custom BiometryModel** combining:
    - **Feature Extractor:** 3D U-Net with 3 depth levels.
        - **Channels per Layer:** (16, 32, 64).
    - **Regression Head:**
        - **Adaptive Average Pooling** to reduce spatial dimensions.
        - **Fully Connected Layers:**
            - Linear(32, 128) with ReLU activation.
            - Linear(128, 7) outputs.

Predicted Outputs:

- **Biometric Measurements:** bBIP, sBIP, HV, LCC, TCD.
- **Pathology Classification:** Neurotypical (0) or Pathological (1).
- **Gestational Age.**

Task – 2 Biometry Training Details

Data Handling:

- **Dataset:** Used provided biometry CSV data.
- **Missing Values:** Filled with column means.
- **Label Encoding:** Mapped 'Pathology' to numerical values.

Training Details:

- **Loss Function:** Mean Squared Error (MSE) Loss.
- **Optimizer:** Adam optimizer with learning rate **1e-4**.
- **Batch Size:** 1.
- **Epochs:** 100.
- **Training Time:** Approximately **2 hours** on an **RTX 4090 GPU**.

Integration and Inference Pipeline

Input Preprocessing

- Loaded MRI images and participant metadata.

Segmentation Prediction

- Applied the trained 3D U-Net model.
- Outputs resized to match original image dimensions using SimpleITK.

Biometry Prediction

- Used the BiometryModel to predict biometric measurements.
- Outputs saved in the required TSV format.

Post-Processing

- Ensured outputs matched spatial properties of inputs.

Results and Key Achievements

Segmentation Performance:

• Successfully segmented fetal brain tissues across all classes.
• Handled variability in data from different institutions.

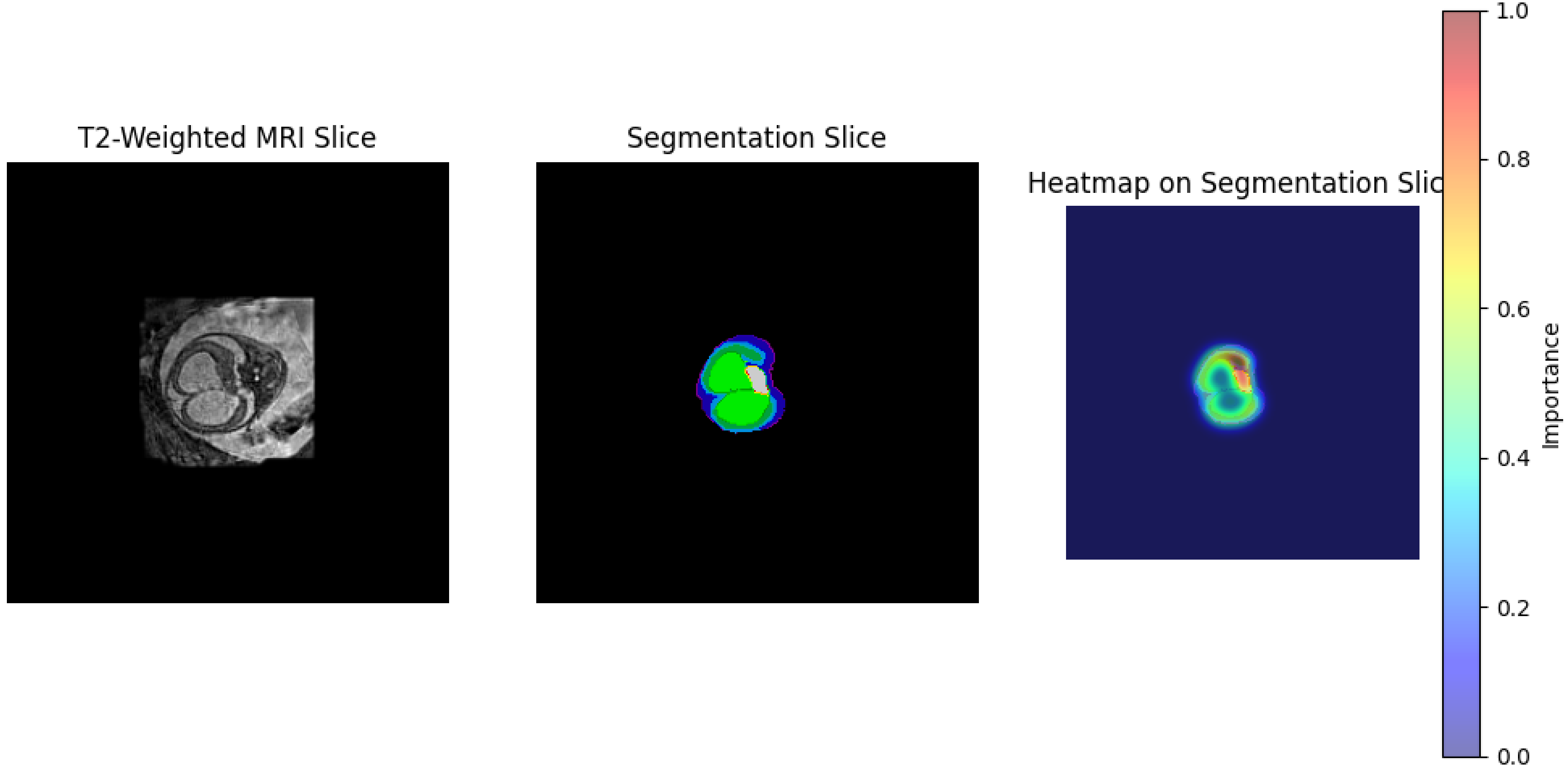
Biometry Prediction:

• Accurately predicted biometric measurements.
• Integrated pathology classification and gestational age estimation.

Model Efficiency:

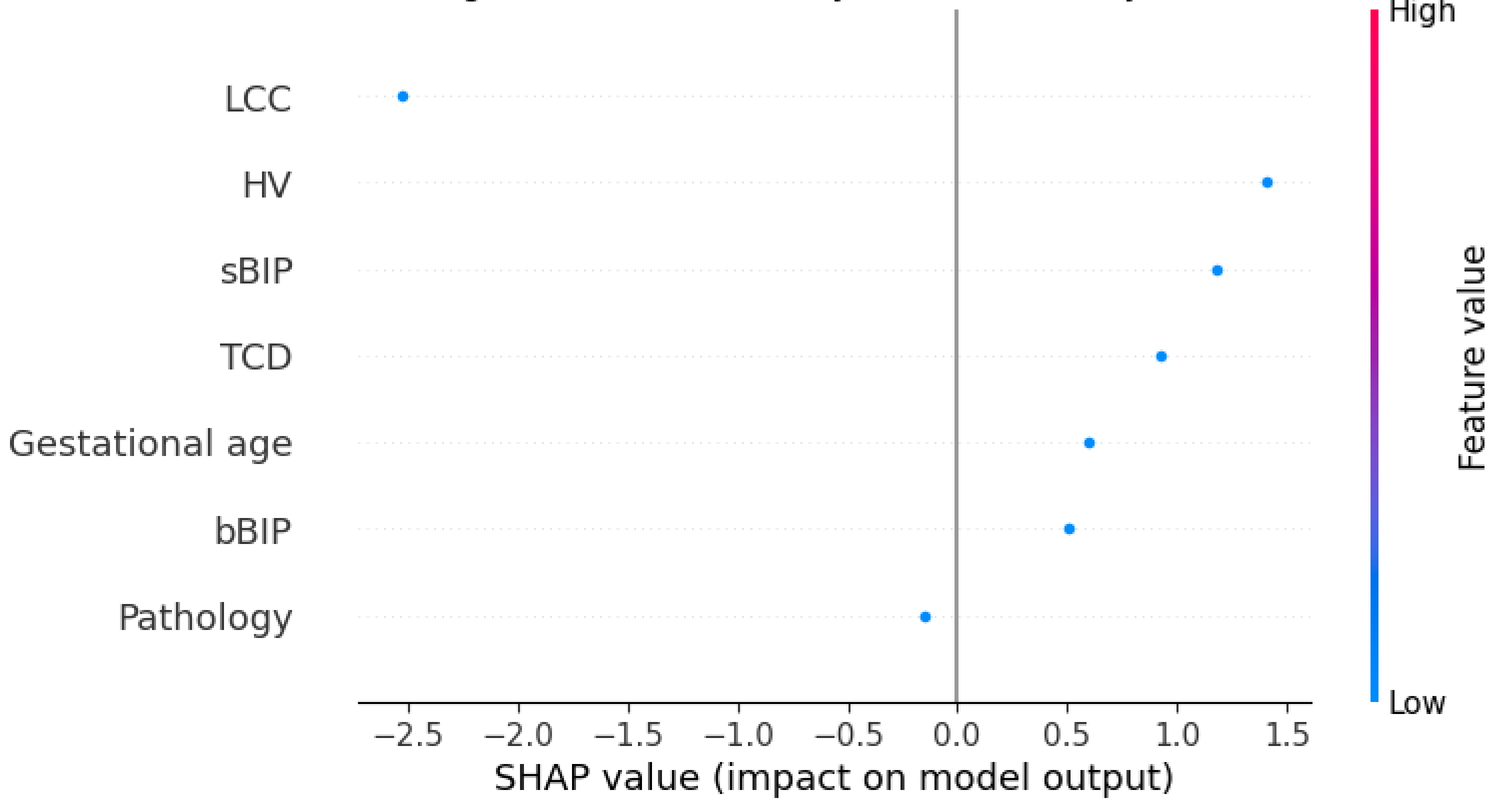
• Optimized architectures for resource constraints.
• Efficient training times despite large 3D data.

Future Enhancement – Explainable AI



Future Enhancement – Explainable AI

Figure 2: SHAP Summary Plot for Biometry Data



Conclusion

Innovations:

• Developed tailored 3D U-Net models for both segmentation and biometry tasks.
• Implemented effective preprocessing and augmentation techniques.
• Addressed challenges of data variability and computational limitations.

Contributions:

• Provided a cohesive pipeline for fetal brain MRI analysis.
• Potential to aid in early detection and diagnosis in clinical settings.

Acknowledgement

FeTA Challenge Organizers: For providing the dataset and platform.

Frameworks and Libraries:

- **PyTorch 2.3**
- **MONAI 1.3.2**
- **SimpleITK 2.3.1**

References:

- **MONAI Framework:** Cardoso et al., "MONAI: An open-source framework for deep learning in healthcare", arXiv:2211.02701.
- **U-Net Architecture:** Ronneberger et al., "U-Net: Convolutional Networks for Biomedical Image Segmentation", MICCAI 2015.

Thank You