Methodology Development: Nuchal Translucency measurement and thickness detection

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1. Objective

To design, develop, and evaluate a state-of-the-art AI-driven pipeline capable of accurately detecting and measuring NT thickness from fetal ultrasound images, ensuring clinical-grade performance for real-world use.

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1. Data Collection and Preparation

1.1 Dataset Acquisition

- **Clinical Collaborations**: Establish partnerships with hospitals and diagnostic centers to collect fetal ultrasound images taken between 11–14 weeks of gestation.
- **Public Data**: Source data from publicly available repositories such as Kaggle, MURA, or specialized obstetric datasets if accessible.
- **Ethical Clearance**: Ensure compliance with HIPAA or GDPR regulations for patient confidentiality, obtaining necessary permissions for clinical data usage.

1.2 Data Preprocessing

- **Normalization**: Normalize image intensities to account for varying ultrasound machine settings.
- **Contrast Enhancement**: Employ adaptive histogram equalization or CLAHE to enhance NT visibility.
- **Noise Reduction**:
    - Apply Gaussian filters or wavelet-based denoising techniques.
    - Use anisotropic diffusion for edge-preserving noise suppression.
- **ROI Extraction**:
    - Use bounding box annotations (manual or automated) to isolate NT regions.

    - Employ sliding window methods or patch-based segmentation to focus on critical areas.
- **Artifact Removal**: Remove speckle noise and irrelevant artifacts using domain-specific techniques like median filtering or deep-learning-based despeckling models.

2. Model Development

2.1 Baseline Models

- Extract hand-crafted features (e.g., texture, edge, and geometric features) using HOG, Gabor filters, or wavelet transforms.
- Train and evaluate traditional classifiers such as:
    - **Support Vector Machines (SVM)** for binary classification.
    - **Random Forests** for feature importance analysis.

2.2 Deep Learning Architectures

2.2.1 Segmentation Models

- **U-Net**: Use as a baseline for NT segmentation due to its success in biomedical image processing.
- **Refinements**: Incorporate residual connections or multi-scale attention to improve NT boundary detection.
- **Variants**:
    - ResU-Net: Integrate ResNet blocks for better feature representation.
    - Attention U-Net: Embed attention gates for precise NT region delineation in noisy images.

2.2.2 Classification Models

- **EfficientNet**: Utilize this lightweight and scalable architecture for NT thickness classification.

- **Vision Transformers (ViT)**: Fine-tune for high-resolution images and capture long-range dependencies in ultrasound images.

2.3 Generative Models

- **GANs (Generative Adversarial Networks)**:
  - Generate synthetic NT images to balance dataset class distribution.
  - Use StyleGAN for high-quality image generation with domain-specific adjustments.
- **Data Augmentation GANs**: Augment existing datasets to simulate variations in image quality, orientation, and fetal positioning.

2.4 Attention Mechanisms

- Integrate attention modules to prioritize NT regions:
  - Use **Squeeze-and-Excitation Networks** to enhance feature importance adaptively.
  - Incorporate **Transformer-Based Architectures** for learning from low-quality or noisy images.

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3. Training and Validation

3.1 Data Splitting and Augmentation

- Divide dataset into:
  - **Training Set**: 70%
  - **Validation Set**: 15%
  - **Testing Set**: 15%
- Apply robust data augmentation strategies:
  - Geometric: Random rotations, flipping, and scaling.
  - Color: Intensity shifting and gamma correction.
  - Noise Injection: Simulate real-world ultrasound conditions.

3.2 Training Strategy

- **Optimizer**: Use AdamW or SGD with learning rate warm-up and cosine annealing.
- **Loss Functions**:
  - **Segmentation**: Combined loss of Dice and Binary Cross-Entropy (BCE) for balanced segmentation.
  - **Classification**: Weighted cross-entropy to handle class imbalances.
- **Regularization**:
  - Dropout and weight decay to mitigate overfitting.
  - Use early stopping based on validation loss.

3.3 Validation and Cross-Validation

- Perform K-fold cross-validation to evaluate model robustness.
- Monitor metrics like Dice Score, IoU, AUROC, sensitivity, and specificity across folds.

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4. Evaluation Metrics and Benchmarking

4.1 Segmentation Metrics

- Dice Similarity Coefficient (DSC): Evaluate overlap between predicted and ground-truth NT regions.
- Intersection over Union (IoU): Measure accuracy of segmentation boundaries.

4.2 Classification Metrics

- Area Under Receiver Operating Characteristic Curve (AUROC).
- Sensitivity and specificity for identifying abnormal NT values.

4.3 Computational Efficiency

- Inference time on real-time ultrasound images.
- Resource utilization (e.g., GPU/CPU memory, latency).

4.4 Clinical Benchmarking

- Compare automated measurements against clinician-annotated NT thickness using Bland-Altman analysis or similar statistical tests.

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5. Deployment Pipeline

5.1 End-to-End System

- Integrate modules for preprocessing, segmentation, classification, and post-processing in a unified pipeline.
- Optimize for edge devices to enable deployment in clinical ultrasound machines.

5.2 Real-World Validation

- Evaluate system on unseen clinical datasets to ensure robustness across varied demographics and equipment.
- Conduct usability studies with radiologists to refine user interface and workflow integration.

5.3 Deployment Formats

- Develop as a standalone desktop/mobile application.
- Collaborate with ultrasound device manufacturers to integrate as a plug-in or firmware update.

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6. Iterative Refinement and Feedback Loop

6.1 Continuous Learning

- Use active learning to incorporate edge cases and mislabeled instances into retraining pipelines.
- Employ federated learning for privacy-preserving model updates using clinical feedback.

6.2 Collaboration with Clinicians

- Regularly gather qualitative feedback from radiologists and obstetricians.
- Address interpretability concerns using explainable AI (XAI) techniques to highlight NT region predictions.

6.3 Enhancements

- Investigate multi-task learning to predict additional markers (e.g., nasal bone length) simultaneously.
- Explore self-supervised learning to maximize utility of unlabeled ultrasound data.
