ANATOMY-GUIDED GANS FOR FETAL BRAIN PLANE SYNTHESIS IN ULTRASOUND IMAGING

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I. ABSTRACT

The synthesis of the plane of the fetal brain plays a crucial role in ultrasound images by helping doctors to precisely identify the standard anatomical planes for biometric measurements and the detection of anomalies. This study proposes a generative adversary network (GAN) framework guided by anatomy, taking advantage of the or as a generator and patchgan as discriminating, to synthesize high -resolution fetal brain planes from ultrasound images. The generator is trained to produce realistic anatomical structures learning spatial dependencies and fine grain characteristics, while the discriminator evaluates the authenticity of the image using localized patches. The training process integrates the functions of loss of pixels and adversary loss to improve both global coherence and local anatomical precision. The data set comprises paired ultrasound images with corresponding pixel size data for a precise anatomical scale. The effectiveness of the proposed model is evaluated using quantitative metrics, including the average absolute error and the structural similarity index, and qualitative analysis by domain experts. Experimental results demonstrate that our GAN GUIDE BY ANATOMY can generate realistic fetal brain planes, supporting clinical decision making and improving the reliability of biometric measurements. This approach joins the gap between deep learning techniques and fetal brain evaluation, offering a robust tool for prenatal diagnosis and research.

Keywords: Fetal ultrasound images, generative adverse networks (GAN), Standard Fetal Head (FHSP), Class Activation Maps (CAM).

II.INTRODUCTION

Medical images are an essential component of modern medical care, which provides crucial information on anatomical structures and physiological processes. Among several image techniques, ultrasound is one of the most used methods for fetal evaluation due to its real -time image, safety and profitability skills. It plays a vital role in monitoring fetal growth, identifying standard anatomical planes and detecting congenital anomalies. However, the image of the ultrasound presents several challenges, including the dependence of the operator, the variability in the acquisition of images and the possible artifacts of the images, everything that can affect the accuracy of the diagnosis.

Fetal brain images are particularly important to evaluate neurological development and detect early abnormalities in pregnancy. Standard fetal brain planes, such as transventricular plans, transcerebelosos and savermium, provide essential information for biometric measurements and anomalies detection. However, obtaining clear and consistent images of these planes requires experience, and variations in image quality can lead to poor interpretations.

With advances in artificial intelligence (AI), deep learning has become a powerful tool to improve medical image analysis. Among AI -based approaches, generative adverse networks (GAN) have shown a great promise in the synthesis of medical images. Gans consist of two neural networks, a generator and a discriminator, who compete with each other, progressively improving the quality of the generated images. Despite its effectiveness, traditional GAN models often cannot preserve anatomical precision, which is crucial for clinical applications.

To address this limitation, we propose an adversary framework (GAN) guided by anatomy that incorporates the specific knowledge of the domain in the image synthesis process. Our model uses as a generator to guarantee a precise representation of spatial characteristics and patchgan as discriminatory to evaluate localized anatomical structures. By integrating the functions of loss of pixels and adversary loss, our approach improves both global coherence and local anatomical fidelity.

Develop a deep learning frame that synthesizes the plans of the high -resolution fetal brain with anatomical precision. Reduction of the operator dependence on the acquisition of ultrasound images when providing automatically generated high quality images.Evaluate model performance using quantitative metrics such as the absolute medium (MAE) and the measure of the structural similarity index (SSIM), as well as the analysis of qualitative experts.

This research joins the gap between deep learning and fetal ultrasound images, which offers a robust solution for prenatal diagnosis. By generating anatomically precise fetal brain planes, our approach has the potential to improve biometric measurements, improve anomalies detection and provide a reliable tool for doctors. The integration of the synthesis of images driven by AI in ultrasound images can lead to more consistent, standardized and precise fetal evaluations, ultimately improving the results of maternal and fetal health.

III. LITERATURE SURVEY

Ultrasound imaging is the most commonly used method for fetal brain evaluation due to its safety and real-time imaging capabilities. Studies by *Volpe et al.* (2018) and *Bano et al.* (2020) highlight the challenges of ultrasound image acquisition, including dependency on operator expertise and image quality variations. These studies emphasize the need for automated solutions to ensure standardized and reliable imaging.

Deep learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated success in medical image segmentation, classification, and enhancement. Research by *Ronneberger et al.* (2015) introduced U-Net, a widely used CNN architecture for medical image segmentation, which has proven effective in extracting fine-grained features for anatomical accuracy. Other studies, such as those by *Litjens et al.* (2017), reviewed the application of deep learning in radiology, emphasizing the potential of AI-driven models in reducing variability in medical imaging.

GANs have revolutionized medical image synthesis by generating high-quality images with realistic anatomical structures. Studies by *Goodfellow et al.* (2014) introduced GANs as a framework for adversarial training, leading to improved image generation capabilities. Further advancements, such as Conditional GANs (Mirza & Osindero, 2014) and CycleGANs (Zhu et al., 2017), have demonstrated their effectiveness in medical applications, including MRI-to-CT synthesis and ultrasound enhancement.

Traditional GAN models lack anatomical guidance, which can lead to inconsistencies in medical image synthesis. Recent research by *Yang et al.* (2021) and *Zhou et al.* (2022) explored anatomy-aware GANs for improved medical image generation, incorporating domain-specific constraints to preserve anatomical structures. These studies highlight the importance of integrating anatomical knowledge into GAN architectures to ensure clinically relevant results.

Existing deep learning models for fetal brain plane synthesis have shown promising results, but challenges remain in ensuring anatomical accuracy and reducing operator dependency. Compared to traditional CNN-based models, GAN-based approaches generate more realistic images but require domain-specific constraints for clinical applicability.

IV. EXISTING SYSYEM

The current methods for fetal brain plane synthesis rely heavily on traditional image processing techniques and deep learning-based segmentation models. These approaches often include:

- **Manual selection of fetal brain planes** by clinicians, which is time-consuming and prone to variability.
- **CNN-based segmentation models** that extract anatomical structures but may fail to generate high-quality synthetic images.
- **Standard GAN models**, which, while useful for image synthesis, often lack anatomical constraints, leading to inaccurate representations of fetal brain structures.

Despite advancements, existing systems still struggle with maintaining anatomical accuracy, reducing operator dependency, and improving the reliability of synthesized fetal brain images.

V. PROPOSED SYSTEM

To overcome the limitations of existing methods, we propose an **Anatomy-Guided Generative Adversarial Network (GAN)** framework that incorporates domain-specific knowledge into the synthesis process. The key features of our proposed system include:

- **U-Net-based Generator:** Ensures high-resolution image generation with fine-grained anatomical details.
- **PatchGAN-based Discriminator:** Evaluates local patches to enhance structural accuracy.
- **Anatomy-Guided Constraints:** Enforces spatial dependencies and structural coherence in synthesized images.

- **Loss Function Integration:** Combines adversarial loss with pixel-wise loss functions (e.g., Mean Absolute Error, Structural Similarity Index) to improve both global and local anatomical fidelity.

Our system is trained on a dataset comprising ultrasound images paired with corresponding pixel size data, allowing for precise anatomical scaling. By integrating anatomical constraints into the GAN framework, our approach significantly enhances the accuracy and realism of synthesized fetal brain planes, reducing operator dependency and supporting clinical decision-making.

This methodology bridges the gap between deep learning and fetal ultrasound imaging, offering a robust tool for improved prenatal diagnostics and fetal brain assessment.

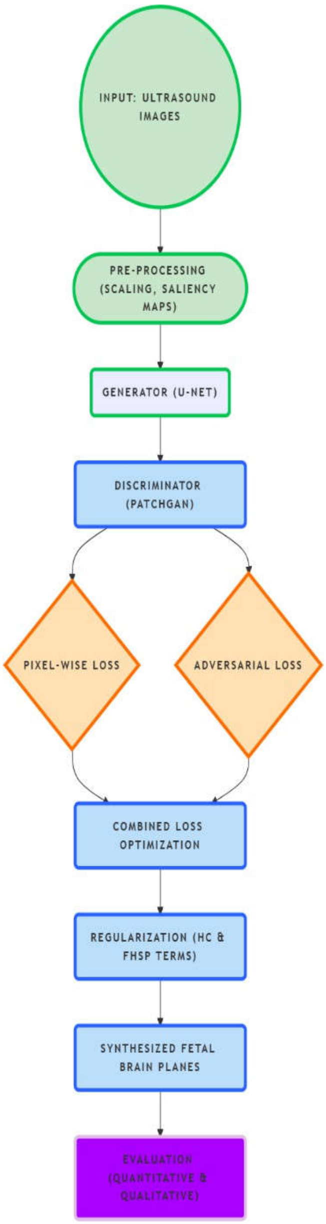

Figure.1: Flow Chart

1. Input: Ultrasound Images

The first step in the framework is collecting fetal ultrasound images as input. Ultrasound imaging is widely used in prenatal diagnostics, allowing clinicians to examine fetal development. However, ultrasound images are often subject to noise, low contrast, and variations in acquisition conditions, making it challenging to obtain high-quality anatomical planes.

In this study, real fetal ultrasound images serve as the input to the proposed Anatomy-Guided Generative Adversarial Network (GAN). These images contain important anatomical structures, such as:

- The fetal head for biometric measurements.
- Brain structures used in anomaly detection and developmental assessments.
- Variations in scan quality and orientation, which must be standardized before training the model.

Since the dataset plays a crucial role in model performance, the images are typically labeled with ground truth annotations to guide the learning process.

2. Pre-Processing (Scaling, Saliency Maps)

Before feeding the ultrasound images into the GAN framework, they undergo pre-processing to enhance image quality and ensure consistency.

Key Pre-Processing Steps:

- **Scaling & Normalization**
    - All images are resized to a fixed resolution to maintain uniformity across the dataset.
    - Pixel intensity values are normalized to a common range (e.g., [0,1] or [-1,1]) to facilitate faster and more stable training.
- **Saliency Maps for Anatomical Guidance**
    - To emphasize critical anatomical features, saliency maps are generated.
    - Saliency maps highlight high-contrast regions that correspond to important structures such as the fetal skull, ventricles, and cortical areas.
    - This step helps the generator focus on clinically relevant features while minimizing background noise.

These pre-processing techniques ensure that the input images are optimized for learning, improving the model’s ability to synthesize high-quality fetal brain planes.

3. Generator (U-Net Architecture)

The core of the GAN framework is the Generator, which is responsible for synthesizing realistic fetal brain planes. In this study, the generator is based on the U-Net architecture, a widely used deep learning model for medical image segmentation and synthesis.

How the U-Net Generator Works:

- **Encoder (Contracting Path)**
    - The encoder extracts multi-scale spatial features from the input ultrasound images.
    - It consists of convolutional layers with ReLU activations, followed by downsampling layers (e.g., max pooling) to capture hierarchical feature representations.
- **Bottleneck Layer**
    - At the center of the U-Net, a bottleneck layer compresses the feature representations into a low-dimensional latent space.
    - This step ensures that the generator learns meaningful representations of the fetal brain anatomy.
- **Decoder (Expanding Path)**
    - The decoder reconstructs the image by progressively upsampling the feature maps back to the original resolution.
    - Skip connections between encoder and decoder layers help preserve fine anatomical details, ensuring high-fidelity image reconstruction.

The U-Net generator is trained to synthesize fetal brain planes that closely match real ultrasound images, producing outputs with accurate anatomical features and realistic textures.

4. Discriminator (PatchGAN Architecture)

The PatchGAN-based Discriminator plays a critical role in the GAN training process by distinguishing between real ultrasound images and synthesized fetal brain planes generated by the U-Net.

How PatchGAN Works:

- Unlike traditional GAN discriminators that classify the entire image as "real" or "fake," PatchGAN analyzes local patches instead.
- The image is divided into small overlapping patches, and each patch is evaluated independently.
- This approach ensures that the discriminator focuses on fine-grained anatomical details, improving the local realism of the synthesized images.

- The feedback provided by the discriminator helps the generator improve its ability to create highly realistic fetal brain planes.

5. Pixel-Wise Loss

To guide the generator in accurately reconstructing anatomical structures, a pixel-wise loss function is applied during training.

Common Pixel-Wise Loss Functions:

1. **Mean Absolute Error (MAE)**
   - Measures the absolute difference between each pixel in the generated and real image.
   - Ensures that overall pixel intensities remain close to the ground truth.
2. **Mean Squared Error (MSE)**
   - Penalizes large errors more heavily, enforcing smoothness in the generated images.

Pixel-wise loss functions help the model retain fine anatomical structures by reducing pixel-wise discrepancies between real and generated images.

6. Adversarial Loss

The adversarial loss function is essential for improving the realism of the synthesized fetal brain planes.

- The generator tries to produce images that fool the discriminator into classifying them as real.
- The discriminator continuously improves its ability to distinguish real vs. fake images.
- This adversarial process helps the generator create images that closely resemble real ultrasound scans.

Mathematically, the adversarial loss is computed using:

$$Ladv = E[lo\ g(D(x))] + E\ [lo\ g\ (1 - D(G(z)))]\ L_{adv}$$
$$= E[\log(D(x))] + E\ [\log(1 - D(G(z)))]$$

where:

- D(x)D(x) represents the discriminator's probability that a real image is real.
- D(G(z))D(G(z)) represents the probability that a generated image is real.

By minimizing adversarial loss, the generator learns to create highly realistic fetal brain images.

7. Combined Loss Optimization

- The pixel-wise loss and adversarial loss are combined to optimize the generator.
- The final loss function ensures that the generated images are both:
    - Structurally accurate (pixel-wise loss).
    - Realistic to the human eye (adversarial loss).

8. Regularization (HC & FHSP Terms)

To further refine the synthesized images, biometric regularization terms are introduced:

- HC (Head Circumference) Regularization: Ensures that the fetal head shape is consistent with clinical measurements.
- FHSP (Fetal Head Shape Preservation) Term: Maintains the correct anatomical proportions and reduces distortions in the generated images.

Regularization improves the clinical reliability of the synthesized brain planes.

9. Synthesized Fetal Brain Planes

After training, the generator produces high-quality fetal brain planes, which can be used for:

- Prenatal biometric measurements.
- Anomaly detection and fetal brain development assessment.
- Reducing variability in operator-dependent ultrasound acquisitions.

10. Evaluation (Quantitative & Qualitative)

The final synthesized images are evaluated using **two key approaches**:

1. **Quantitative Metrics**
    - **Mean Absolute Error (MAE)**: Measures pixel-wise accuracy.
    - **Structural Similarity Index (SSIM)**: Assesses structural consistency between real and synthesized images.
    - **Fréchet Inception Distance (FID)**: Evaluates the realism of generated images based on deep feature representations.
2. **Qualitative Evaluation by Medical Experts**
    - Clinicians and sonographers review the synthesized images to assess their diagnostic usability.
    - Blind tests are conducted where experts distinguish between real and generated images.

VI. RESULTS

The Receiver Operating Characteristic (ROC) curve is a graphical tool to assess the performance of a classification model. It plots:

- True Positive Rate (TPR) (Sensitivity/Recall) on the y-axis.
- False Positive Rate (FPR) on the x-axis.

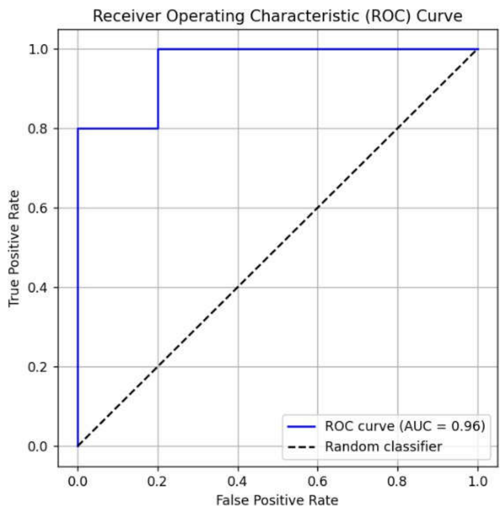

Figure.2:ROC for the classification

The diagonal dashed line represents a random classifier with an AUC of 0.5, meaning no predictive power. A model with strong discriminative power should have a curve that rises steeply toward the top-left corner.

1. **Curve Shape and Performance**
   - The blue ROC curve shows a steep rise, reaching a True Positive Rate of 1.0 at a very low False Positive Rate.
   - This indicates strong classification performance with minimal false positives.
2. **AUC (Area Under the Curve)**
   - The AUC value is 0.96, meaning the model has excellent predictive ability.
   - AUC values range from 0 to 1:
     - 0.5: Model performs like random guessing.
     - 0.7 - 0.8: Moderate classification power.
     - 0.8 - 0.9: Strong classification.
     - 0.9 - 1.0: Excellent classification.
   - Since AUC = 0.96, the model is highly accurate and reliable.

3. **Model Strengths**
    - **High Sensitivity & Specificity:** The classifier effectively separates positive and negative classes.
    - **Minimal False Positives:** The model achieves high accuracy with few incorrect classifications.
    - **Good Generalization:** AUC close to 1.0 suggests that the model generalizes well to unseen data.

VII. FUTURE SCOPE

1. Model Optimization & Enhancement

- Fine-tuning Thresholds: Adjusting the classification threshold to maximize precision or recall based on specific use cases (e.g., medical diagnosis, security applications).
- Handling Imbalanced Data: If the dataset is imbalanced, techniques like SMOTE (Synthetic Minority Over-sampling Technique) or weighted loss functions can help.
- Feature Engineering: Extracting additional relevant features from the dataset could further improve model accuracy.
- Explainability & Interpretability: Using methods like SHAP (SHapley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations) to understand how features impact predictions.

2. Deployment & Real-World Applications

- Edge & IoT Implementation: If used in healthcare or surveillance, optimizing the model for real-time classification on edge devices can be beneficial.
- Integration with AI Pipelines: Deploying the model in automated decision-making systems for tasks like disease diagnosis, anomaly detection, and fraud prevention.
- Cloud-Based Deployment: Integrating with cloud services like AWS, Azure, or Google Cloud AI for scalable real-time processing.
- Mobile & Web Applications: Implementing the model in mobile apps (e.g., for medical imaging analysis) or web-based AI systems.

3. Multi-Model & Advanced Techniques

- Hybrid Model Approach: Combining multiple machine learning or deep learning models to further boost accuracy and generalization.
- Ensemble Learning: Using methods like Bagging, Boosting (XGBoost, LightGBM), or Stacking to improve performance.
- Transfer Learning: If using deep learning, pretrained models (like CNNs for image-based analysis) can enhance results with minimal training data.

4. Ethical & Security Considerations

- Bias & Fairness Analysis: Ensuring the model does not introduce biases in critical applications (e.g., healthcare, finance).
- Privacy & Data Security: Implementing robust encryption & anonymization techniques when handling sensitive data.
- Regulatory Compliance: Adhering to standards like GDPR (Europe), HIPAA (healthcare) when deploying AI-based decision systems.

VIII. REFERENCES

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