1. Introduction:

- Brief background on the importance of fetal head circumference measurement in prenatal care.
- Introduction to the use of sonography images for this purpose.
- Statement of the problem and motivation for employing deep learning techniques.

The introduction section provides a brief background on the importance of fetal head circumference measurement in prenatal care, establishing the context and significance of the research.

Introduction:

Fetal head circumference measurement is a critical parameter in prenatal care, playing a pivotal role in assessing the well-being and development of the unborn child. The accurate determination of fetal head circumference is essential for monitoring fetal growth, identifying potential abnormalities, and ensuring the overall health of both the fetus and the expectant mother.

Accurate measurements of the fetal head circumference are particularly crucial for predicting gestational age and identifying potential intrauterine growth restrictions. These measurements serve as key indicators for healthcare professionals, aiding in the timely detection of developmental issues or complications that may require intervention.

Traditional methods of fetal head circumference measurement, while established, may be subject to limitations and inaccuracies. As a response to these challenges, the integration of advanced imaging technologies, specifically sonography, has emerged as a promising avenue for enhancing precision in fetal measurements.

In this context, the application of deep learning techniques to analyze sonography images for fetal head circumference measurement holds significant potential. By leveraging the power of artificial intelligence, we aim to improve the accuracy and reliability of these measurements, thereby advancing the capabilities of prenatal care and contributing to better health outcomes for both mothers and infants. This research addresses the need for more robust and efficient methods in fetal head circumference measurement, aligning with the broader goal of enhancing the quality of prenatal healthcare practices.

Introduction to Ultrasonic Images in Fetal Head Circumference Measurement:

Ultrasonic imaging has become a cornerstone in prenatal care, offering a non-invasive and safe method for visualizing the developing fetus. In particular, the utilization of ultrasonic images for fetal head circumference measurement provides healthcare professionals with valuable insights into fetal development and overall well-being.

Ultrasonic imaging, commonly known as sonography, involves the emission of high-frequency sound waves into the body, which then bounce back to create detailed images of internal structures. This imaging modality is widely preferred in obstetrics due to its real-time capabilities, lack of ionizing radiation, and ability to capture dynamic fetal movements.

The fetal head is a key anatomical region for assessment during pregnancy, and ultrasonic images offer a clear visualization of the fetal cranium, facilitating accurate measurements of the head circumference. This non-invasive approach allows for repeated measurements throughout the gestational period, aiding in the monitoring of fetal growth and the identification of any potential abnormalities.

Moreover, the accessibility and safety of ultrasonic imaging make it an integral component of routine prenatal examinations. Expectant parents benefit from the ability to visually connect with their developing child, while healthcare providers rely on these images to make informed decisions regarding the health and development of the fetus.

Despite the advantages of ultrasonic imaging, the accuracy of measurements can be influenced by various factors, including image quality, operator skill, and anatomical variations. This research addresses these challenges by incorporating deep learning techniques to analyze ultrasonic images systematically. By harnessing the power of artificial intelligence, we aim to enhance the precision and reliability of fetal head circumference measurements, ultimately contributing to more effective and informed prenatal care practices.

The statement of the problem and motivation for employing deep learning techniques in fetal head circumference measurement is a critical aspect of the introduction, highlighting the challenges and the rationale behind the chosen approach.

Statement of the Problem:

Accurate measurement of fetal head circumference is pivotal in prenatal care for assessing gestational age, identifying growth abnormalities, and ensuring the well-being of both the fetus and the expectant mother. However, traditional methods of measurement may be prone to inaccuracies due to variations in operator expertise, image quality, and anatomical complexities.

Inaccurate or imprecise measurements can lead to misdiagnoses, potentially resulting in inadequate prenatal interventions or unnecessary medical procedures. Therefore, there is a pressing need for a more reliable and automated approach to fetal head circumference measurement that mitigates the limitations associated with manual techniques.

Motivation for Employing Deep Learning Techniques:

The motivation for employing deep learning techniques stems from the transformative potential of artificial intelligence in medical image analysis. Deep learning, a subset of machine learning, excels at learning intricate patterns and features from large datasets, making it well-suited for complex tasks such as image recognition and segmentation.

In the context of fetal head circumference measurement, deep learning can bring automation, objectivity, and consistency to the process. By training a deep learning model on a diverse set of ultrasonic images, the system can learn to identify and measure the fetal head circumference with a high degree of accuracy, reducing the dependence on human interpretation.

Moreover, deep learning models have demonstrated the ability to adapt and generalize well to variations in imaging conditions and anatomical structures. This adaptability is crucial in the inherently diverse and dynamic field of obstetric imaging.

The integration of deep learning techniques in this research is driven by the aspiration to enhance the precision and efficiency of fetal head circumference measurements, ultimately improving the quality of prenatal care. By automating this process, we aim to provide healthcare professionals with a valuable tool that can contribute to more reliable and timely assessments, leading to better outcomes for both mothers and infants.

Literature Review

- Overview of existing methods for fetal head circumference measurement.
- Discussion on challenges and limitations in traditional approaches.
- Survey of recent advancements in deep learning for medical image analysis, specifically in sonography.

Overview of Fetal Head Circumference Measurement Methods

Fetal head circumference measurement is a critical aspect of prenatal care, and various methods have been employed over the years to achieve accurate and reliable results. This literature review provides an overview of existing methods, highlighting their strengths, limitations, and the evolving landscape of fetal biometry.

1. Manual Measurement Techniques:

Historically, manual measurements using ultrasound have been the standard practice in prenatal care.

Common methods include the use of ellipsoidal or spheroidal models, where the sonographer manually traces the fetal head outline on ultrasound images.

Despite being widely utilized, manual techniques are subject to inter-operator variability and may be time-consuming.

2. Semi-Automated Approaches:

With advancements in image processing, semi-automated methods have emerged.

These methods often involve a combination of manual initialization by the operator and subsequent automated algorithms for contour detection.

While reducing operator dependence, semi-automated approaches may still be influenced by subjective decisions during initialization.

3. Computer-Aided Techniques:

Computer-aided techniques leverage computational algorithms for automated fetal head circumference measurement.

These methods aim to eliminate operator bias by relying on sophisticated image analysis algorithms.

Some challenges include adapting to various fetal positions and accounting for image artifacts that can affect accuracy.

4. 3D Imaging and Volumetric Approaches:

Three-dimensional (3D) imaging techniques have gained attention for fetal biometry, offering volumetric information.

Volumetric approaches provide a more comprehensive assessment of the fetal head and may enhance accuracy compared to traditional 2D methods.

However, challenges such as increased data complexity and computational requirements need consideration.

5. Machine Learning and Deep Learning:

Recent literature highlights the increasing application of machine learning and deep learning in fetal biometry.

Machine learning models, including traditional regression-based approaches, have shown promise in automating fetal measurements.

Deep learning, with its ability to automatically learn features from data, presents a cutting-edge avenue for improving the accuracy and robustness of fetal head circumference measurement.

6. Challenges and Future Directions:

Common challenges across methods include variability in fetal positioning, image quality issues, and the need for standardization.

The literature suggests the ongoing need for more comprehensive datasets and rigorous validation studies to assess the generalizability of different measurement techniques.

This literature review underscores the evolution of fetal head circumference measurement methods, from manual approaches to the incorporation of advanced computational and deep learning techniques. As we delve into deep learning for this study, understanding the landscape of existing methods informs the rationale and potential contributions of our research.

Challenges and Limitations in Traditional Approaches to Fetal Head Circumference Measurement:

Traditional approaches to fetal head circumference measurement, primarily relying on manual and semi-automated techniques, have played a crucial role in prenatal care. However, these methods are not without their challenges and limitations, which this discussion aims to illuminate.

1. Inter-Operator Variability:

One of the primary challenges in traditional approaches is the inherent subjectivity and variability introduced by different operators.

Manual measurements, reliant on sonographer expertise, can lead to discrepancies in fetal head circumference values due to variations in contour delineation.

2. Time-Consuming Procedures:

Manual measurements are often time-consuming, requiring careful tracing of fetal head contours on ultrasound images.

The labor-intensive nature of these procedures may lead to fatigue and potential errors, particularly in busy clinical settings where time is a critical factor.

3. Dependency on Operator Skill:

The accuracy of traditional approaches is heavily dependent on the skill and experience of the operator.

Inexperienced sonographers may encounter difficulties in obtaining precise measurements, introducing a potential source of error.

4. Sensitivity to Fetal Positioning:

Fetal positioning during ultrasound examinations can significantly impact the accuracy of traditional measurements.

Variations in fetal presentation may result in distorted images, affecting the reliability of circumference measurements.

5. Limited Adaptability to Anatomical Variations:

Traditional approaches may struggle to adapt to anatomical variations in fetal head shape.

The use of simplified models, such as ellipsoidal or spheroidal shapes, may not accurately represent the diversity of fetal anatomies.

6. Inability to Handle Image Artifacts:

Ultrasound images may suffer from artifacts such as shadowing or noise, particularly in challenging imaging conditions.

Traditional methods may struggle to robustly handle these artifacts, leading to potential inaccuracies in measurements.

7. Lack of Standardization:

Standardization of measurement techniques is often lacking in traditional approaches, contributing to variability across healthcare institutions.

This lack of standardization hinders the comparability and consistency of fetal head circumference data.

8. Limited 3D Information:

Traditional 2D imaging approaches may not capture the full three-dimensional complexity of the fetal head.

This limitation can impact the accuracy of measurements, especially when dealing with irregularly shaped heads or subtle anomalies.

9. Challenges in Handling Large Datasets:

As medical datasets grow in size and complexity, traditional approaches may face challenges in efficiently handling and analyzing large volumes of ultrasound data.

Understanding and addressing these challenges in traditional approaches underscore the necessity for innovative solutions. The shift towards advanced computational methods, including machine learning and deep learning, presents an opportunity to overcome these limitations and significantly improve the accuracy and reliability of fetal head circumference measurements in prenatal care.

Survey of Recent Advancements in Deep Learning for Medical Image Analysis, with a Focus on Ultrasound Image Segmentation:

In recent years, deep learning has emerged as a powerful tool in medical image analysis, particularly for ultrasound image segmentation. This survey explores the latest advancements, methodologies, and outcomes in leveraging deep learning techniques for accurate and efficient segmentation of structures in medical ultrasound images.

1. U-Net Architecture and Variants:

- U-Net, a convolutional neural network (CNN) architecture designed for biomedical image segmentation, has become a standard in ultrasound image analysis.
- Recent advancements include variations of U-Net with modifications in skip connections, encoder-decoder architecture, and attention mechanisms for improved performance.

2. Multi-Modal Fusion for Improved Segmentation:

- Integration of multi-modal information, such as combining B-mode and Doppler ultrasound data, has shown promise in enhancing segmentation accuracy.

- Deep learning models designed to fuse information from multiple modalities contribute to a more comprehensive understanding of anatomical structures.

3. Transfer Learning Strategies:

- Transfer learning, leveraging pre-trained models on large datasets, has gained popularity for ultrasound image segmentation.
- Models pre-trained on diverse datasets, like ImageNet, are fine-tuned for specific ultrasound segmentation tasks, improving generalization and performance.

4. Attention Mechanisms in Segmentation Networks:

- Attention mechanisms, such as self-attention and spatial attention, have been integrated into segmentation networks.
- These mechanisms enhance the model's focus on relevant regions, improving segmentation accuracy and robustness.

5. Generative Adversarial Networks (GANs) for Data Augmentation:

- GANs have been utilized for generating synthetic ultrasound images, aiding in data augmentation.
- Augmenting datasets with GAN-generated images enhances the model's ability to generalize to different imaging conditions and improves segmentation results.

6. 3D Convolutional Neural Networks (CNNs) for Volumetric Segmentation:

- 3D CNNs have been employed for volumetric segmentation in ultrasound images, providing a more comprehensive analysis of three-dimensional structures.
- These networks show promise in tasks such as organ segmentation and volumetric measurements.

7. Real-time Segmentation and Edge Computing:

- Efforts have been directed towards developing real-time segmentation models suitable for edge computing platforms.
- Real-time segmentation is crucial for applications such as intraoperative guidance and point-of-care diagnostics.

8. Challenges and Future Directions:

- Challenges include the scarcity of annotated ultrasound datasets, interpretability of complex models, and addressing issues related to variable image quality.

- Future directions include the exploration of unsupervised and semi-supervised learning methods, improved model explain ability, and the integration of domain-specific knowledge into segmentation networks.

This survey underscores the rapid progress in applying deep learning techniques to ultrasound image segmentation, offering a glimpse into the potential transformative impact on medical diagnostics and treatment planning. The ongoing advancements in this field hold promise for more accurate and efficient segmentation, ultimately improving patient outcomes in medical imaging.

Objectives:

The objectives of the project are clearly defined goals aimed at enhancing accuracy, efficiency, and reliability in fetal head circumference measurements through the application of deep learning techniques, with a specific focus on ultrasound image segmentation. The project is conducted using a dataset comprising 999 ultrasound images.

1. Develop a Deep Learning Model:

- Design and implement a deep learning model tailored for ultrasound image segmentation, with a specific emphasis on fetal head circumference measurement.
- Explore and select a suitable architecture, considering factors such as convolutional neural networks (CNNs), attention mechanisms, and 3D CNNs for volumetric segmentation.

2. Dataset Preparation and Augmentation:

- Preprocess and augment the dataset containing 999 ultrasound images to enhance model robustness and generalization.
- Implement data augmentation techniques, including rotation, scaling, and flipping, to diversify the dataset and simulate variations encountered in real-world scenarios.

3. Training and Optimization:

- Train the deep learning model on the prepared dataset, optimizing hyperparameters to achieve optimal performance.
- Implement regularization techniques and fine-tune the model to prevent overfitting and enhance generalization capabilities.

4. Evaluation Metrics:

- Define and employ appropriate evaluation metrics to quantitatively assess the performance of the deep learning model.
- Metrics may include accuracy, precision, recall, F1 score, and Intersection over Union (IoU) to comprehensively evaluate segmentation results.

5. Comparison with Traditional Methods:

- Compare the proposed deep learning approach with traditional methods for fetal head circumference measurement using ultrasound images.
- Quantitatively analyze and present the differences in accuracy, efficiency, and reliability between the deep learning model and traditional segmentation techniques.

6. Generalization Testing:

- Assess the generalization capabilities of the developed deep learning model by evaluating its performance on external datasets or unseen data.
- Ensure that the model demonstrates consistent and reliable fetal head circumference measurements across a variety of imaging conditions.

7. Real-Time Inference and Efficiency:

- Implement real-time inference capabilities to assess the efficiency of the deep learning model in providing prompt measurements during clinical applications.
- Analyze and optimize the computational efficiency of the model for potential deployment in point-of-care scenarios.

8. User-Friendly Interface Integration (Optional):

- If applicable, explore the integration of the developed deep learning model into a user-friendly interface for healthcare professionals.
- Ensure ease of use and interpretability, facilitating seamless adoption in clinical settings.

9. Documentation and Reporting:

- Document the methodology, implementation details, and results comprehensively for transparent reporting.
- Prepare a detailed report highlighting the achievements, challenges, and future directions for the proposed deep learning-based fetal head circumference measurement approach.
- By addressing these objectives, the project aims to contribute to the improvement of accuracy, efficiency, and reliability in fetal head circumference measurements through the innovative application of deep learning in ultrasound image segmentation.

Methodology:

- Description of the dataset used, including acquisition details and preprocessing steps.
- Explanation of the deep learning architecture chosen for the task, highlighting its relevance and suitability.

- Training and validation procedures for the model, specifying hyperparameters and evaluation metrics.

Need to write about it.

Detailed Breakdown of Deep Learning Model Architecture for Ultrasound Image Segmentation :

The proposed deep learning model for ultrasound image segmentation focuses on accurately measuring fetal head circumference. The architecture is designed to handle the complexities of ultrasound images and extract precise segmentation maps. Below is a detailed breakdown of the components and their roles within the model.

1. Input Layer:
Role : The input layer receives ultrasound images from the dataset, typically in 2D format.

Processing : Images are represented as matrices of pixel values. The input layer provides the foundational data for subsequent feature extraction and segmentation.

2. Convolutional Encoder:
Role : This segment extracts hierarchical features from the input images.

Processing : Convolutional layers with filters detect patterns and edges, capturing both low and high-level features. Down-sampling layers (e.g., pooling or stride convolutions) reduce spatial dimensions.

3. Bottleneck/Neck Layer:
Role : This layer acts as a bottleneck, compressing feature representations.

Processing : Utilizes deeper convolutional layers to capture intricate details. It condenses information, enabling the model to learn more abstract and complex features.

4. Decoding Path - Up sampling Blocks :

Role : Up sampling blocks help in reconstructing spatial information lost during encoding.

Processing : Transposed convolutions or upsampling layers expand the feature maps, gradually recovering spatial resolution. Skip connections are established between corresponding encoding and decoding layers, aiding in the reconstruction of fine details.

5. Skip Connections:
Role : Addressing vanishing gradient issues and facilitating better information flow.

Processing : Concatenates feature maps from encoding layers to decoding layers. This integration ensures that the model retains both low-level and high-level features, aiding in precise segmentation.

6. Feature Concatenation:
Role : Merging features from different scales to enhance segmentation accuracy.

Processing : Concatenates feature maps from the decoding path with corresponding feature maps from the encoding path. This fusion of multi-scale information contributes to a more robust representation.

7. Attention Mechanisms (Optional):
Role : Enhancing focus on relevant regions, particularly useful for handling complex structures.

Processing : Attention gates or mechanisms are incorporated to selectively weigh feature maps, emphasizing salient regions crucial for accurate segmentation.

8. Output Layer - Sigmoid Activation:
Role : Producing segmentation maps with pixel-wise probabilities.
Processing : The final layer utilizes a sigmoid activation function, generating pixel-wise probability maps. Each pixel represents the likelihood of belonging to the target class (fetal head) or background.

9. Loss Function - Binary Cross-Entropy:
Role : Quantifying the difference between predicted and ground truth segmentation maps.

Processing : Binary cross-entropy loss is employed to measure the dissimilarity between predicted probabilities and the actual binary segmentation maps. This guides the model during training to improve segmentation accuracy.

10. Optimization and Training:
Role: Adjusting model parameters to minimize the loss function.

Processing: Optimizers such as Adam or SGD are employed to update weights iteratively. Training involves forward and backward passes, adjusting the model to improve segmentation performance.

11. Evaluation Metrics:
Role: Assessing the model's performance during training and validation.

Processing: Metrics like accuracy, precision, recall, F1 score, and IoU are computed to evaluate the segmentation model's effectiveness in accurately delineating the fetal head.

This detailed breakdown highlights the comprehensive architecture of the deep learning model, emphasizing its ability to process ultrasound images for accurate fetal head circumference segmentation. The integration of encoding, decoding, skip connections, and attention mechanisms collectively contributes to the model's capacity to handle the intricacies of ultrasound image data.

Modifications to CNN and VGGNet Architecture for Fetal Head Circumference Segmentation :

In adapting Convolutional Neural Networks (CNN) and VGGNet architectures for the specific task of fetal head circumference segmentation in ultrasound images, several modifications have been implemented. To address the unique characteristics of ultrasound data, the input preprocessing stage involves normalization and contrast adjustment tailored to enhance the visibility of fetal structures. For feature extraction layers, both architectures have undergone customization – CNN's initial convolutional layers are designed to capture ultrasound-specific low-level features, while adjustments in VGGNet's convolutional layers aim to balance the extraction of generic and ultrasound-specific features. Skip connections have been introduced to facilitate the fusion of multi-scale features, allowing the model to capture both global context and fine details. Attention mechanisms are integrated into both architectures to emphasize relevant regions, enhancing the focus on critical structures within ultrasound images. Additionally, modifications in stride and pooling layers optimize the models for varying fetal head sizes and positions. The output layer is tailored with a sigmoid activation function to generate probability maps for accurate pixel-wise segmentation. These adaptations collectively optimize CNN and VGGNet architectures for the nuanced task of fetal head circumference segmentation in ultrasound images, ensuring enhanced accuracy and reliability in prenatal care applications.

For the specific application of fetal head circumference segmentation in ultrasound images, certain modifications and adaptations have been made to both Convolutional Neural Network (CNN) and VGGNet architectures. These adjustments are tailored to address the unique characteristics of ultrasound data and enhance the model's ability to accurately segment fetal heads. Below are the key modifications:

Input Preprocessing:

CNN: Integration of preprocessing steps specific to ultrasound images, such as normalization and contrast adjustment, to enhance the visibility of fetal structures.

VGGNet: Similar preprocessing steps, but with additional emphasis on preserving fine details critical for accurate segmentation.

Feature Extraction Layers:
CNN: Customization of the initial convolutional layers to capture low-level features relevant to ultrasound structures, considering speckle patterns and edge details.

VGGNet: Adjustments in the number of filters in the initial convolutional layers to balance the extraction of both generic and ultrasound-specific features.

Skip Connections :

CNN: Incorporation of skip connections between encoding and decoding paths to facilitate the fusion of multi-scale features, enabling the model to capture both global context and fine details.

VGGNet: Modification to include skip connections, adapting the VGG architecture to exploit hierarchical features for improved segmentation accuracy.

Attention Mechanisms:
CNN: Introduction of attention mechanisms to emphasize relevant regions in the ultrasound images, enhancing the model's focus on critical structures.

VGGNet: Integration of attention mechanisms within specific blocks of the VGGNet architecture, allowing the model to selectively attend to informative regions during segmentation.

Adjustment of Stride and Pooling:
CNN: Optimization of convolutional layer strides to account for varying fetal head sizes and positions within ultrasound images.

VGGNet: Modification of pooling layers to adapt to the scale of features in ultrasound data, ensuring effective downsampling without loss of critical details.

Output Layer and Activation Function:
CNN: Utilization of a specialized output layer with a sigmoid activation function to generate probability maps for accurate pixel-wise segmentation.

VGGNet: Adaptation of the final layer to accommodate sigmoid activation, aligning with the requirements of binary segmentation in the context of fetal head circumference.

Loss Function Selection:
CNN: Employing a customized loss function, potentially incorporating class-specific weights or penalties to address class imbalance and emphasize the significance of fetal head pixels.

VGGNet: Modification of the loss function to accommodate the unique challenges of fetal head segmentation in ultrasound images.

These modifications to both CNN and VGGNet architectures aim to optimize the models for the specific challenges posed by ultrasound data. The adjustments enhance the networks' capability to accurately segment fetal heads, considering the nuances of imaging characteristics and the importance of precise measurements in prenatal care.

The implementation of the fetal head circumference segmentation model involves a combination of software and hardware resources to facilitate the training, validation, and evaluation processes. Here is an overview of the software and hardware components utilized in the implementation:

Implementation Overview:

Software:

- **Deep Learning Framework:**
    - **TensorFlow or PyTorch:** The choice between TensorFlow and PyTorch depends on the familiarity and preferences of the development team. Both frameworks offer robust support for building and training deep learning models, and their flexibility makes them suitable for customizing the architecture.
- **Python Programming Language:**
    - **NumPy, Pandas, Matplotlib:** Fundamental libraries for data manipulation, visualization, and numerical computations. These are essential for preparing the dataset, analyzing results, and ensuring seamless integration with the chosen deep learning framework.

- **Image Processing Libraries:**

    - **OpenCV:** Utilized for pre-processing ultrasound images, including normalization, contrast adjustment, and other image enhancements required for optimal model performance.
- **Visualization Tools:**
    - **TensorBoard (TensorFlow) or Visdom (PyTorch):** Used for real-time visualization of training metrics, loss curves, and model architecture. These tools aid in monitoring the training process and identifying potential issues.
- **Model Interpretability (Optional):**
    - **LIME, SHAP, Grad-CAM:** Depending on the interpretability requirements, tools like LIME (Local Interpretable Model-agnostic Explanations), SHAP (SHapley Additive exPlanations), or Grad-CAM (Gradient-weighted Class Activation Mapping) can provide insights into the model's decision-making process.
- **Version Control:**
    - **Git:** Essential for collaborative development, version tracking, and managing code changes. Git repositories enable seamless collaboration among team members.

Hardware:

- **CPU:**
    - **Multi-Core CPU (e.g., Intel Core or AMD Ryzen):** While GPU acceleration is crucial for training deep learning models, a powerful multi-core CPU is beneficial for data preprocessing, model initialization, and other non-GPU-intensive tasks.
- **Memory (RAM):**
    - **Sufficient RAM (e.g., 16GB or more):** Ensures smooth handling of large datasets during preprocessing and model training. Ample RAM is particularly important when dealing with 3D images or volumetric data.
- **Storage:**
    - **SSD or HDD Storage:** Fast storage is necessary for quick data access during training. SSDs are preferred for their faster read and write speeds, contributing to improved training efficiency.
- **Cloud Services (Optional):**
    - **AWS, Google Cloud, or Azure:** Cloud computing platforms can be employed for extensive computational resources, especially for large-scale training or when GPU availability is limited locally.

This software and hardware infrastructure forms the foundation for the successful implementation of the fetal head circumference segmentation model, enabling efficient model development, training, and evaluation. The choice of specific tools and resources can be tailored based on project requirements, team expertise, and available computational resources.

Step-by-step description of the code implementation, including data loading, model training, and testing

Results and Discussion:

- **Presentation of quantitative results, including accuracy, precision, recall, and other relevant metrics.**