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CAD System Utilizing UNet and Hough Transform for Automated Measurement of Fetal Head Circumference and Age in 2D Ultrasound Images

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Abstract: Two-dimensional (2D) medical ultrasound is a widely used imaging modality for the anatomical and functional assessment of fetal development due to its low cost, availability, real-time capability, and the absence of radiation hazards. Head circumference (HC) is an essential biometric to measure fetal growth. However, the low signal-to-noise ratio in ultrasound imaging can make it difficult for clinicians to identify the fetal plane correctly. Additionally, manually measuring HC can be expensive, involving accurately placing three minor and major parameter points from the ultrasound machine. To address these issues, research has been conducted to develop an automated system for measuring HC. This study presents a computer-aided diagnosis (CAD) system for the automatic measurement of fetal HC and fetal age using hybrid feature extraction. Using Convolutional Neural Networks (CNNs), self-supervised learning (SSL), vision transformers (ViTs), UNet deep learning model for segmentation, and Hough transform to measure performance, this study achieved higher performance compared to previous studies with a Dice similarity coefficient (DSC) of 97.23 ± 2.78, an average distance factor (ADF) of 2.8 ± 2.93 mm, a Jaccard Index of 88.57 ± 3.79, and an accuracy of 97.2%. After that, we enhance UNet using an attention mechanism that achieved a Dice coefficient of 98.5 ± 2.5, an ADF of 2.4 ± 2.8 mm, and an accuracy of 98.1%. This system provides a more cost-effective and accurate measurement of HC, aiding clinicians in assessing fetal development.

Keywords: fetal ultrasound, segmentation, head circumference, UNet, Hough transform

1. Introduction

There has been much research on developing automated methods for measuring head circumference (HC) using two-dimensional (2D) ultrasound pictures. Because of their low cost, widespread availability, real-time capability, and absence of radiation exposure, 2D medical ultrasonography (USG) machines have become the primary imaging modality for the surveillance of fetal anatomy and function [1]. Usually, a standard ultrasound examination is advised between weeks 18 and 22 of pregnancy. 2D ultrasound devices create diagnostic images doctors use to assess fetal development stages [2]. The embryonic growth process can be evaluated through multiple qualitative and quantitative research approaches. Qualitative analysis of fetal heart physiology serves as one investigative method. Through quantitative analysis, fetal development assessment utilizes biometric data to estimate gestational age and measure fetal weight in order to detect potential fetal anomalies. Accurate weight measurements combined with age estimation remain necessary to provide top-level care for the unborn child. For a person's biometric profile, their facial features include forehead width, arm measurements, and leg length. Accurately determining fetal gestational age depends on using HC because this method provides reliable data about fetal HC [3].

Healthcare professionals currently conduct HC assessments in their regular patient measurement routine through semi-automatic methods. A doctor's success depends on their understanding of anatomical positioning to position the probe correctly. Medical staff must precisely determine and categorize maternal tissue on the fetal plane before using the ellipse parameter calipers. When calipers are correctly placed, the USG machine generates an ellipse and calculates its dimensional radius. A low signal-to-noise ratio leads to frequent difficulties for clinicians in separating the maternal tissue from the fetal plane. Medical practitioners across all levels find it challenging and time-consuming to measure fetal biometry manually [4]. Medical personnel use automatic methods to measure patient HC by joining selected spots on ultrasound pictures' main and smallest elliptical axes. Computing the ellipse circumference allows researchers to define an accurate HC representation. The interpretation process encounters difficulties associated with ultrasound image noise elements, such as speckles and artifacts, which demand expert-level knowledge from observers. Observational differences in manual HC marking between practitioners result in wide measurement variations [5].

The objective and more accurate fetal HC measurement could be achieved by automated methods. The fetal HC is typically determined

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by identifying the fetal head region of interest (RoI), fitting an ellipse inside the RoI, and finally calculating the HC using the adjusted circumference. The technique utilized in this paper for fetal head RoI localization is a multiscale classifier, such as the Haar cascaded classifier algorithm family. This work optimizes the ellipse-fitting algorithm for a candidate RoI in the fetal skull. Ellipse fitting algorithms often fall into one of three broad classes: statistical, heuristic, or hybrid approaches; methods based on clustering or voting; and methods based on geometric or algebraic least squares [6]. The noniterative algebraic methods are well-suited for real-time applications due to their comparatively easy solutions. When dealing with broken or partially occluded ellipses, their performance can be reduced due to their sensitivity to outlier noise and bias in the estimations. On the other hand, geometric methods are more resilient to noise but necessitate iterative calculations that get progressively more complex. Even though it relies heavily on a predefined training dataset and is not as robust, the clustering method can find ellipses quickly. The Hough transform approaches that rely on voting are better at avoiding occlusions, but they need an exponentially large amount of computation. Statistical models may fail when faced with extremely high noise levels, and the Kalman filtering approach favors high curvature fits. A normal distribution model or the Hough transform in conjunction with least square minimization requires a lot of computing power [7]. Machine learning methods have recently been increasingly applied to fetal biometry in order to analyze high-level features from ultrasound image data. Convolutional Neural Network (CNN) model applications are widely used for medical [8], geographical [9, 10], and other fields, and their usefulness has been proven. Li et al. [11] used a random forest classifier to localize the fetal head and employed phase symmetry and ellipse fitting to fit the HC ellipse for measurement. However, this approach requires prior knowledge of the gestational age and ultrasound scanning depth. Irene et al. [12] suggested a CNN in order to identify boundaries of the fetal head in ultrasound images that classifies every pixel as one of four groups, including maternal network (horizontal patterns), upper head boundary (concave arcs), lower head boundary (convex arcs), and background. On polar-transformed images, they used a UNet model and they were able to complete this multi-class segmentation successfully.

This paper studies the methodology in determining fetal head measurements and estimating gestational age using 2D ultrasound images. With the latest improvements in ultrasound imaging technology, we provide a thorough analysis of the methods employed for fetal head assessment and age estimation in 2D ultrasound scans. We investigate multiple ultrasound measurement techniques for fetal heads and age measurements within 2D ultrasound images. Section 2 shows related work; Section 3 explains our proposed method; Section 4 shows the simulation results of our proposed model; and Section 5 shows our conclusion and future works.

2. Related Works

Segmenting the fetal head from ultrasound images is a critical yet challenging task due to variations in head size and shape and the inherently low contrast of ultrasound scans. Recent studies have explored various deep-learning architectures to enhance segmentation accuracy.

The authors introduced Directed Acyclic Graph (DAG)-based extension of the V-Net (DAG V-Net), a deep learning-based method specifically designed for fetal head segmentation and HC measurement in 2D ultrasound images. Their approach achieved a mean Dice similarity coefficient (DSC) of 97.93%, demonstrating the effectiveness of V-Net-based architectures in capturing fine details [13].

Similarly, other researchers proposed the Scale Attention Pyramid Network (SAPNet), which leveraged an attention mechanism to enhance feature extraction, achieving a DSC of 97.94%. This highlights the significant role of attention-based architectures in improving segmentation accuracy [14].

The authors adopted a regression CNN for fetal head delineation, integrating ellipse fitting with an iterative closest point algorithm and a random sample consensus (RANSAC) method. Their approach attained a DSC of 97.95%, showcasing the advantages of combining deep learning with geometric modelling for precise HC measurement [15].

This paper introduced the Fast Double Branch Network (FDB-Net), which utilized dilated convolutions to segment the fetal skull in ultrasound images, achieving a DSC of 97.98%. The use of dilated convolutions proved effective in capturing both fine details and broader contextual information [16].

Researchers explored a region-based convolutional approach using Mask-R2CNN for fetal head segmentation, achieving a Hausdorff Distance (HD) absolute difference (AD) of 1.95 mm, highlighting the significance of region-based deep learning models for more precise medical imaging [17].

Ghelich Oghli et al. [18] developed a CNN-based architecture for HC biometry measurement, attaining a DSC of 97.20% and demonstrating the feasibility of CNN-based segmentation for automatic fetal biometry analysis. Fiorentino et al. employed a regression CNN for HC segmentation, achieving an AD of 1.90 mm, further validating the accuracy of deep learning models for HC estimation [19].

Several studies have enhanced traditional architectures to improve segmentation accuracy. Ashkani Chenarlogh et al. [20] introduced a modified UNet for fetal head segmentation, achieving a DSC of 97.62%, demonstrating that optimizing UNet architectures can significantly refine segmentation results. Farsana and Kowsalya [21] employed a dilated multi-scale LinkNet model with a merged self-attention mechanism, reaching a DSC of 96.37%, reinforcing the effectiveness of attention mechanisms in segmentation. Additionally, Zeng et al. [22] proposed a fully CNN-based model incorporating multiple design elements, achieving a DSC of 97.61% and an HD AD of 1.97 mm, further demonstrating the efficacy of advanced CNN models in fetal head segmentation.

These studies collectively highlight the importance of integrating attention mechanisms, dilated convolutions, and advanced CNN architectures in order to enhance segmentation accuracy. Building on these advancements, our proposed method employs a hybrid approach that combines Convolutional Neural Networks (CNNs), self-supervised learning (SSL), and vision transformers (ViTs) while integrating an attention-enhanced UNet. This approach ensures more effective feature extraction and improved segmentation performance, addressing the challenges posed by low-contrast ultrasound images and variations in fetal head morphology.

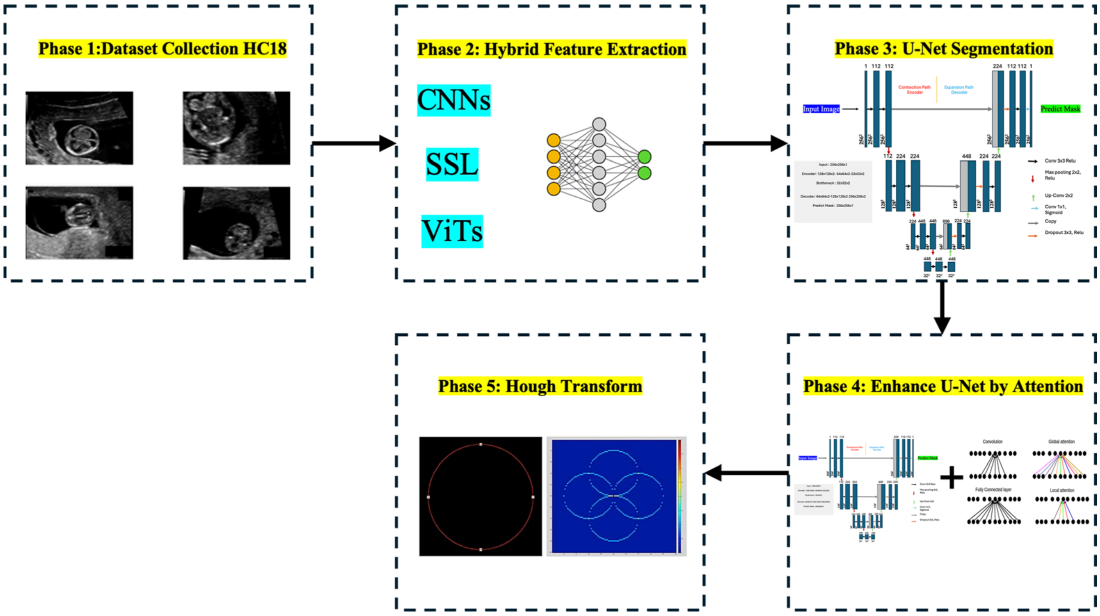
3. Materials and Methods

The section describes the procedures for building an automatic system that measures fetal HC from 2D ultrasound images. The methodology structure consists of four sequential steps that begin with dataset collection followed by hybrid CNN along with SSL combined with ViTs for feature extraction. Then, the steps proceed to segment the fetal head using the UNet deep learning model, which measures the size with the Hough transform, as illustrated in Figure 1. Each stage of the procedure contains specific methods to measure HC efficiently, which enhances clinical decision-making capabilities.

3.1. Phase 1: dataset collection

We used the publicly available HC18 dataset [23], hosted on the Grand Challenge platform, which contains 1,334 2D ultrasound pictures

Figure 1
Methodology of study



of fetal heads. We employed 999 images for training purposes and 335 images for testing purposes. Each image features specific data due to its resolution of 800 × 540 pixels per picture, while pixel widths vary from 0.052 to 0.326 mm. The dataset called HC18 functions as a standard research tool for tracking fetal growth because it contains ongoing HC data from numerous pregnancy cases. Our computer-aided diagnosis (CAD) system benefits from this dataset structure to achieve generalization across different gestational ages along with pregnancy circumstances. The photographic data includes direct measurements of HC that researchers took from the predefined "standard plane" area of the fetal head. System measurements are accurate and in line with clinical standards as they are focused on this plane. The HC18 provides better convenience through a larger collection of maternal and fetal measurement variables, including age, body mass index (BMI), and ethnicity. All pregnancy results, such as small-for-gestational-age (SGA) and low birth weight and full-term and preterm births, are present in the dataset to support extensive fetal development analysis, as Figure 2 shows examples of the data samples.

3.2. Phase 2: hybrid feature extraction using CNNs, SSL, and ViTs

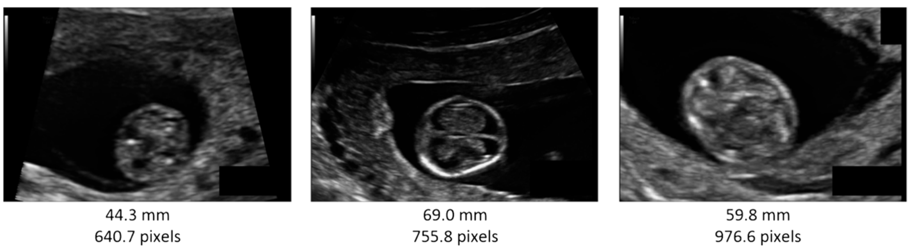
In this phase, we aim to extract relevant and meaningful features from ultrasound images of the fetal head using a combination of modern feature extraction techniques: pretrained CNNs, SSL, and ViTs. The method employs multiple components intended to extract information from images at local scales and integrate it with extended global contextual knowledge [24].

The first step includes utilizing EfficientNet [25] as a pretrained CNN foundation to derive local features from ultrasound images, which encompass edges alongside textures and basic anatomical structures. The models produce feature maps that supply detailed representations of low- and mid-level image features needed to detect fetal head structures. Medical imaging tasks utilize pretrained CNNs because they show effective domain generalization, according to Aggarwal et al. [26] and Kumar et al. [27].

The Momentum Contrast (MoCo) SSL technique [28] is used for feature extraction with a large unlabeled set of ultrasound images. Through SSL, the model develops separate discriminative feature representations by learning from unlabeled data and identifies higher-level image features that supplement the locally extracted features from a CNN. SSL functions as a powerful procedure that teaches representation learning in medical imaging as well as additional domains [29]. SSL assists the model in learning important patterns in ultrasound images by comparing similar and different examples. This allows the model to understand things such as the format and feel the fetal head without unlabelled data. That is difficult when we select manually, but it is necessary to get accurate results. SSL also helps the model work better with new or different images and already supports CNN.

We use ViTs [30] in obtaining long-range dependency modelling while capturing global context because they excel at spatial relationship processing across image regions. The precise location abilities make this technique useful for visualizing anatomical structures with multiple parts, including the fetal skull. The features extracted from both CNN and SSL models enter the ViT for processing so that the model can gain

Figure 2
Samples of dataset



simultaneous comprehension of the whole image. ViTs significantly benefit medical imaging tasks because these models establish connections between global context and distant element dependencies [31, 32].

The combined features extracted from CNN, along with SSL and ViT models, become one unified vector before undergoing refinement through attention mechanisms which emphasize significant features. Research shows that these methods have been proven most beneficial for medical imaging because they enable researchers to concentrate on essential areas of interest [33]. Finally, the fused feature vector proceeds to a neural network with Recurrent Neural Network (RNN)-based architecture or alternative classification, or segmentation structure based on the particular task of fetal head segmentation or disease detection. Medical imaging analysis heavily relies on RNNs because these networks process complex operations with high precision, as reported in Litjens et al. [34].

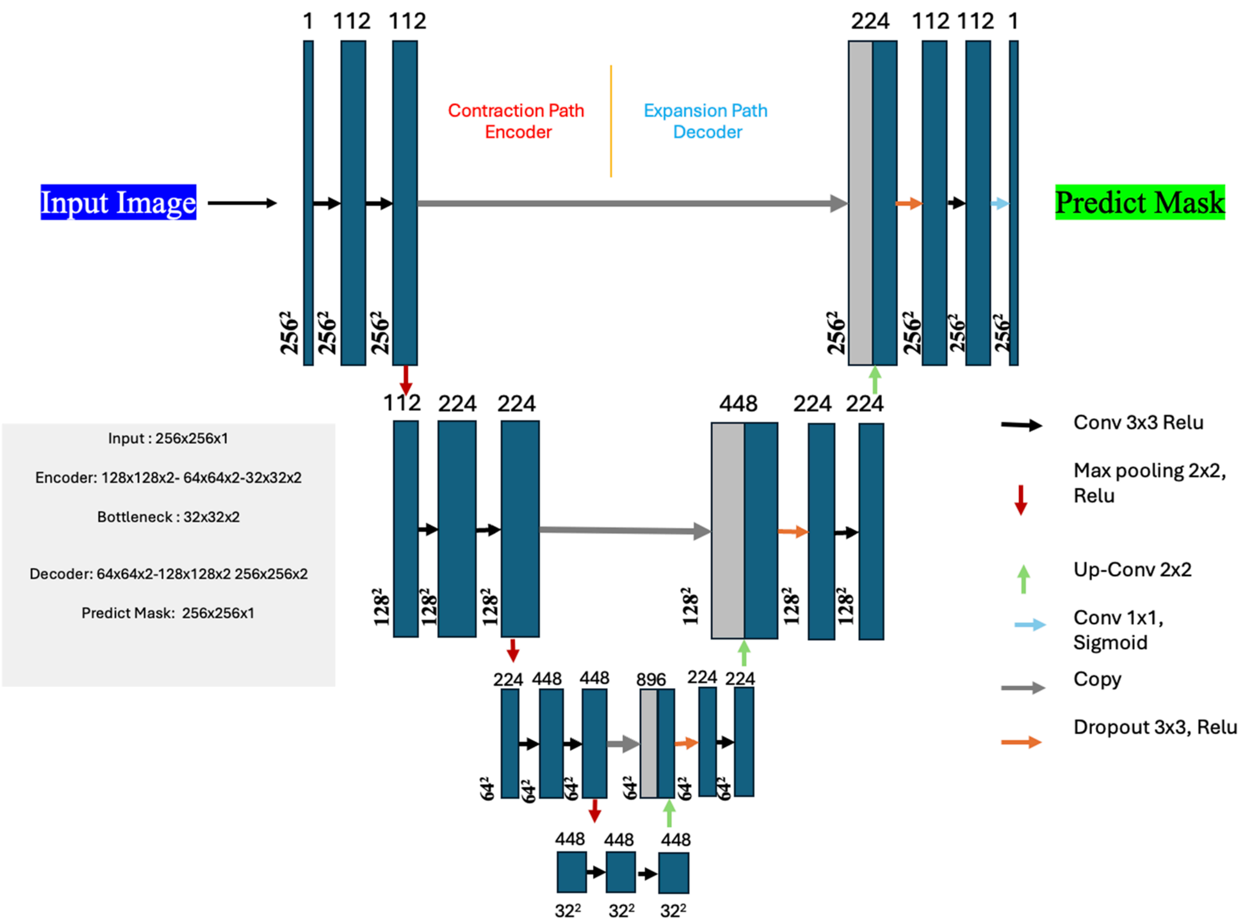
3.3. Phase 3: fetal head segmentation using UNet

After extracting features, they are used to train fetal skull classification. This is done by feeding feature vectors to the classifier to detect patterns in the feature vectors that can be used to identify the fetal skull. This is done through several steps, such as feature selection, training, and testing, until the classifier can classify the fetal skull in a given ultrasound image.

For this purpose, in the first step, we train the UNet network and autoencoder to find and select the fetal head. The UNet architecture is a fully CNN tailored for biomedical picture segmentation [35]. UNet helps us with detailed specifications, and AE helps us with the specific fetal head area. In the next step, we select the head of the fetus and use contouring to improve the result. The tan ellipse and the last step are for the final area of the Feet Ellipse. The UNet network has been used in the proposed CAD systems for fetal HC due to its accurate, fast, and reliable segmentation of various medical images [36]. The proposed modification to traditional UNet architecture focuses on improving fetal HC identification through the methods it introduced. The approach combines hybrid feature extraction using CNNs, SSL, and ViTs before segmentation with contour refinement through elliptical fitting and optimized convolutional layers for ultrasound image feature extraction. This network is very effective in accurately drawing anatomical structures such as fetal HC. UNet can accurately and efficiently diagnose the fetal head. In addition, the classification produced by UNet can be used to compare fetal HC relative to gestational age, which can help determine whether the fetus is developing typically or if there is cause for concern [37]. The UNet deep network used has the following structure in Figure 3.

This U-shaped model specifies that the expansion and contraction routes each include three convolutional blocks. There are two convolution layers: one with a 2 × 2 max-pooling layer and one with a block in the shrinking route. As illustrated in Figure 3, there is another block that includes a 2 × 2 upsampling layer in the broad route, a merge layer that joins the shrinking path with the matching block, a dropout layer, and two convolution layers. Two convolution layers make up the connecting route, as seen in the image. In the end, the layer that produces the pixel class scores is a 1 × 1 convolution layer that uses sigmoid activation and a single filter. In the contraction route of each convolutional layer in blocks 1, 2, and 3, there are 112, 224, and 448

Figure 3
Proposed UNet deep network



filters, respectively. In the expansion path, there are 224, 122, and 122 filters in blocks 5, 6, and 7. Along the connection route, you will find 448 filters for each convolution layer.

Based on Figure 3, the proposed UNet network has two main parts: an encoder and a decoder. The encoder part of the UNet network, proposed by this research to detect fetal HC, is responsible for extracting information from input images and features that can detect fetal HC. This section takes ultrasound images and extracts critical features such as shape, size, texture, colour, and other features after the extracted features are passed to the decoder layers. These are converted into labels or predicted values for the image.

Mathematically, assuming f(x) denotes the input picture, each convolution operation inside the UNet architecture employs a kernel K on f(x) to generate an output feature map, expressed as:

$$\grave{f}(x) = f(x)^{*}K. \tag{1}$$

Equation (1) illustrates how a convolution operation enables the model to extract features concerning space in the input image. If the number of encoder layers in the UNet network is increased, the model's accuracy in detecting fetal HC can be improved. This is because each layer in the encoder increases the network's capacity to gain a deeper understanding of the data, allowing the model to increase its accuracy with better feature extraction capabilities. However, the number of layers increases beyond a certain point. In that case, it can add to the data, leading to poor generalization performance on new data, which we have avoided in the proposed model.

On the other hand, the decoder section in the UNet network is responsible for upgrading the scale of filtered information from the encryption stage. It combines the encoded features from the encoding step with the original image information by repeatedly applying shifted convolutions.

The regular UNet architecture has difficulty working with noisy images with inconsistent contrast levels, producing inferior fetal head segmentation. Our enhanced UNet uses extract feature-based preprocessing to enhance edge structure and reduce background interference, thus solving previous model limitations. Implementing contour refinement techniques produces accurate segmentations when operating under low-contrast conditions.

This upscaling process reconstructs the original input image scale. In the case of the UNet network proposed for fetal HC detection research, the receiver acts as a detector. It magnifies the filtered image to search for the contours and shape of the HC.

Increasing the number of decoder layers in a UNet network can also improve the accuracy of network results because this increase allows the network to extract more specific features from the input data. However, this increase can also lead to increased model complexity and longer training time. In addition, if the number of layers is increased too much, it can lead to overfitting, which reduces the model's generalizability in fetal HC detection.

Upsampling using transpose convolution may be mathematically expressed as:

$$f_{up}(x) = \grave{f}(x)^{*}K. \tag{2}$$

As Equation (2) reads, the transposed convolution feature combines learned encoded features with spatial features of previous layers to recreate an image of the original scale. To detect fetal HC, the decoder enlarges the processed picture to identify the contours and forms of the HC.

The MaxPool layer in the UNet network reduces the spatial resolution of the input feature maps. This size reduction allows for more efficient network training as it reduces the parameters and computations required to process the data without compromising essential properties. For example, if f(x) denotes the input feature map, the max-pooling process may be articulated as:

$$f_{maxpool}(x) = max\{f(x_{i,j})\} \;\; \forall i, j \in window. \tag{3}$$

As Equation (3) mentions, the most outstanding value within a predefined sliding window is chosen in max-pooling, which retains the most pronounced features. In addition, the MaxPool layer is also helpful during segmentation because it brings together the corresponding pixel features and makes learning the segmentation mask for the network easier.

The number of MaxPool layers in the UNet network proposed by this research is essential for fetal HC detection because it affects the model's accuracy. By increasing the encoder layers, the model can more accurately capture the low-level features of images needed for HC detection and reduce false positives and negatives. Additionally, a deeper encoder can produce better segmentation boundaries. This is important for accurate fetal HC detection, as the boundaries of the HC must be determined.

The convolutional layers of UNet facilitate feature extraction by convolving the input data with adjustable filter weights. The convolution process at each layer generates feature maps for detecting fetal HC, given the input feature map $f(x)$ and the filter weights W.

These feature maps traverse following layers to accurately categorize fetal HC.

Augmenting the depth of decoder layers might enhance accuracy by improving the model's capacity to capture intricate features. Nonetheless, it is important to maintain a balance to prevent overfitting, which might adversely affect the generalizability of the fetal HC detection model.

3.4. Phase 4: enhanced UNet using attention mechanism

While the UNet architecture has shown success in fetal head segmentation, its performance can be further improved, particularly in the presence of noisy ultrasound images with low contrast. To enhance the segmentation process, we introduce the Attention-UNet, which integrates attention mechanisms to focus more accurately on the relevant regions of the image, such as the fetal head. The attention mechanism helps the model distinguish between the foreground (the fetal head) and the background, reducing false positives and improving segmentation precision [38].

In this approach, attention gates (AGs) are incorporated into the skip connections between the encoder and the decoder of the UNet [39]. These gates allow the model to selectively focus on the features that are important for fetal head segmentation, filtering out irrelevant or distracting background information. The attention mechanism improves the model's ability to prioritize crucial parts of the image while suppressing noise or irrelevant areas, leading to better segmentation results, particularly in challenging ultrasound images [40].

The Attention-UNet architecture retains the core structure of the original UNet, including the encoder–decoder pathways [41], but adds the attention gates in the skip connections. These gates allow the model to dynamically adjust the focus based on the features being processed, ensuring that the most relevant features for detecting the fetal head are given more weight during training and prediction.

The Attention-UNet is trained using a loss function that combines binary cross-entropy loss and Dice loss [42], which helps improve the model's ability to handle class imbalance and accurately localize the boundaries of the fetal head.

3.5. Phase 5: Hough transform

The Circular Hough Transform (CHT) is an algorithm employed to identify circles within an image. This algorithm leverages edge detection within the image to mathematically identify circles [43]. Because it is highly accurate and efficacious, it is widely used in computer vision and image analysis for applications including object recognition, contour detection, and fetal head detection, which is used in this research.

The Hough transform is an algorithmic solution that can automate measurement of the fetal HC and fetal age in 2D ultrasound images [44]. This application of the algorithmic method enables accurate, reliable measurements of both HC and fetal age, which are critical diagnostic factors for prenatal examinations. The Hough transformation enables the extraction of fetal HC, providing an accurate estimate of fetal age, which is necessary in determining the necessary medical interventions for the developing fetus. To detect a circle through the Hough algorithm, we must specify several parameters, including: the circle's center is located at the coordinates (x_0, y_0); its radius is R.

The equation of the circle can be written as follows:

$$(x - x_0)^2 + (y - y_0)^2 = R^2 \tag{4}$$

Equation (4) shows that every point (x, y) on the circle perimeter fulfils this relation. To detect a circle using Hough's algorithm in an image, the following steps need to be taken: Firstly, we need to identify the edges of the desired image with the help of edge detectors such as Canny. Secondly, we must consider a threshold limit for the optimum values of the radius, both the minimum and maximum. Finally, the process of Hough transformation is applied to identify and locate circles within the image.

In the proposed method, we initially isolate the precise position of the fetus' head, estimate its area, and ultimately account for the fact that the largest diameter present in recorded images is 1.13 times the size of the smaller diameter. In our model, we approximate the fetal head shape using an ellipse, where:

1) a and b represent the semi-major and semi-minor axes, respectively,
2) s represents the elliptical area (in mm²), and
3) p represents the elliptical perimeter (in mm).

The area of the ellipse is calculated by Equation (5) and the perimeter approximated by Equation (6):

$$s = \pi * a * b = \pi * 1.13a^2 \tag{5}$$

$$p = \pi\,(a + b) = \pi * 2.13a^2. \tag{6}$$

In order to isolate the semi-major axis, a, we rewrite Equation (5) as follows, Equation (7):

$$a^2 = \frac{s}{1.13*\pi}. \tag{7}$$

Solving for a, we get Equation (8):

$$a = \sqrt{\frac{s}{1.13*\pi}}. \tag{8}$$

p will be the right-hand side of the area s as in Equation (9):

$$p = 2.13*\pi\sqrt{\frac{s}{1.13*\pi}} \approx 3.5515\sqrt{s}. \tag{9}$$

Once we have measured the fetal HC, we can calculate the probable gestational age of the fetus via a linear correlation, which is universal as seen below in Equation (10):

$$HC = a + b * GA. \tag{10}$$

In this case, GA is gestational age in weeks, and a and b are constants specific to the population. To directly compute gestational age, we apply a modified form commonly taken by prior studies [45], and given in Equation (11), to our study:

$$Age(week) = 1.0787*HC(mm). \tag{11}$$

While the Hough transform is effective for circular shape detection, it has some limitations. Most notably, its performance is sensitive to parameter tuning, such as the range of expected radii and the threshold for edge detection. Incorrect settings may result in false detections or missed features, especially in noisy ultrasound images. Additionally, its computational complexity increases with image resolution and the number of circles to detect. As potential alternatives, methods such as ellipse-specific regression networks, deformable active contours (snakes), or machine learning-based shape fitting techniques may offer better adaptability and robustness in challenging imaging conditions. These approaches can be explored in future work to further improve measurement reliability.

4. Implementation and Simulation

The simulation of the proposed method is done in Python. Python is a more robust language than MATLAB for programming CAD systems for fetal HC. In other words, Python has a greater variety of numerical libraries and a more robust set of language features. Python also allows object-oriented paradigms to structure complex computations or develop larger software projects. Python enables the use of a more significant number of model-based interpretations and problem-solving strategies, which can help improve the accuracy and reliability of the CAD system. Of course, as a more general advantage, Python is more affordable than MATLAB and allows developers to save on license fees. Finally, Python is more accessible for code and development than MATLAB, which may lead to faster system development and deployment. Therefore, it has been used to simulate the proposed method.

4.1. Simulation results

Table 1 describes the simulation results for some sample images, pixel size, and HC size in millimetres (mm).

For example, if we want to estimate the age of the fetus from HC, we use Chen et al.'s [40] article. For example, if the HC was 18.69,

Table 1
Simulation results

Row	Filename	Pixel size (mm)	HC (mm)
1	000_HC.png	0.069136	44.30
2	001_HC.png	0.089659	56.81
3	002_HC.png	0.062033	68.75
4	003_HC.png	0.091291	69.00
5	004_HC.png	0.061240	59.81

the estimated age is 21 weeks. We use the following Equation (11) to estimate the age of the fetus.

In the above relationship, Age(week) is the age of the fetus in weeks. The position of the fetal head is directly related to the area of the fetal head. The simulation results are shown in the following Figure 4.

Figure 5 is the final result after masking to find the HC and age of the fetus.

For this sample image, the estimated age of the fetus is 23 weeks, based on counting the number of white pixels and using the equation provided with scaling.

4.2. Discussion and comparison

Moccia et al. [17] and Sobhaninia et al. [44] have presented a network similar to the proposed method of this research. The accuracy results of the proposed method compared to Moccia et al. [17] and Sobhaninia et al. [44] are presented in the table below. As it is known, the proposed method is more accurate than the other two methods. In fetal ultrasound image segmentation methods with deep learning, average distance factor (ADF) and DSC score parameters are also used for comparison. Table 2 explains the comparison between our proposed model and other studies.

The simulation results show that the proposed UNet method of this research has main advantages for practical applications. In fact, in addition to having a basic and standardized architecture, the proposed method UNet with attention mechanism also has good accuracy. The results presented in the table show that the proposed method has the highest accuracy. Also, the proposed method is simulated on a standard dataset. However, this method still has limitations; one of the most important limitations of the proposed method is the lack of access to a large dataset. If this limitation is removed, it is possible to examine the advantages and disadvantages of the proposed method.

5. Conclusion and Future Works

This study presents a CAD method for the automated assessment of fetal HC and gestational age using 2D ultrasound pictures. We successfully created a system that delivers precise and efficient measurements by utilizing the HC18 dataset and implementing a multi-phase approach, including preprocessing, feature extraction using CNNs, SSL, and ViTs, and segmentation via a UNet deep learning model. The system attained a Dice coefficient of 97.23 ± 2.78, an ADF of 2.8 ± 2.93 mm, and an accuracy of 97.2%, indicating

Figure 4
Simulation results

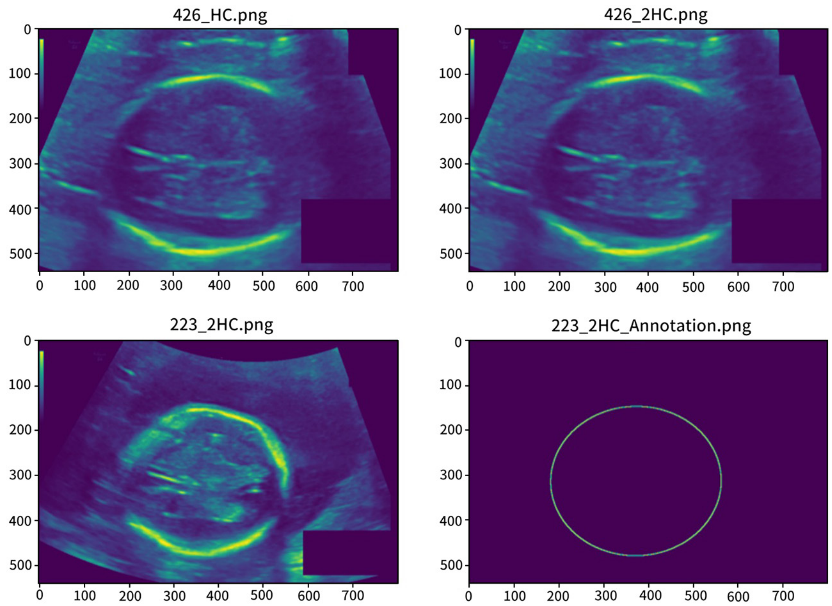


Figure 5
Final result after masking to find head circumference (HC) and fetal age

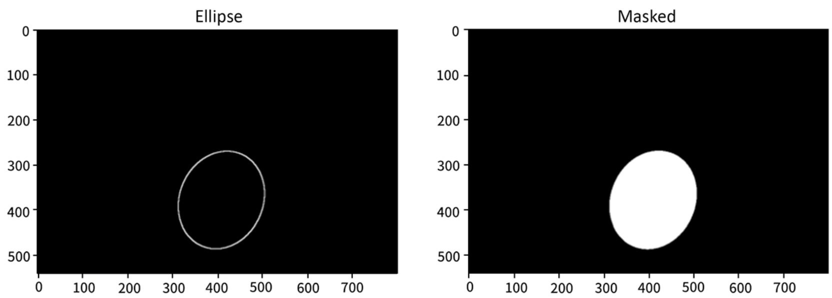


Table 2
Comparison with other studies

Study	Dice parameter	ADF (mm)	Architecture used	Jaccard Index	Acc %
[13]	97.93%	1.77 ± 1.69	Deeply Supervised Attention-Gated V-Net	Nal	Nal
[15]	97.95% ± 1.12%	−0.11 ± 2.67	CNN with Gaussian Map & Ellipse Fitting (RANSAC & ICP)	Nal	Nal
[16]	97.98% ± 1.30%	1.75 ± 1.60	CNN with Double-Branch Structure for Fetal Skull Boundary Segmentation	Nal	Nal
[17]	Nal	1.95 ± 1.92	Mask-R2CNN (Mask-RCNN-based, HC Distance-field Regression)	Nal	Nal
[18]	98%	1.14	Attention MFP-UNet (CNN with Attention Gates and Multi-Feature Pyramid UNet)	Nal	Nal
[19]	97.75 ± 1.32%	1.90 ± 1.76	Regression CNN (Region-proposal CNN for Head Localization + Regression CNN for HC Delineation)	Nal	Nal
[20]	97.45%	Nal	Fast and Accurate UNet	95%	Nal
[21]	96.37%	1.35	Dilated Multi-Scale-LinkNet with Merged Self Attention	Nal	Nal
[22]	97.61%	1.97	Lightweight Deep CNN with Sequential Prediction	Nal	Nal
[44]	96.84±2.89%	2.2±1.87	Hough Transform, Dynamic Programming and an Ellipse Fit	87.13±2.4	97
Our proposal	97.23±2.78%	2.8±2.93	UNet Deep Network	88.57±3.79	97.2
Our proposal	98.5 ± 2.5%	2.4 ± 2.8	UNet + Attention Mechanism	90.2 ± 3.4	98.1

its capability to aid doctors in assessing fetal growth. After that, we enhanced UNet using attention mechanism that achieved a Dice coefficient of 98.5 ± 2.5, an ADF of 2.4 ± 2.8 mm, and an accuracy of 98.1%. This method mitigates the constraints of poor signal-to-noise ratios and human measurement inaccuracies in ultrasonic imaging. The suggested approach provides a cost-efficient and dependable instrument for automating the determination of fetal HC, demonstrating significant promise for clinical use. In the future, we recommend augmenting the dataset to include a more comprehensive array of fetal diseases and gestational ages to enhance the model's generalizability.

Furthermore, integrating sophisticated picture augmentation methods and hybrid deep learning frameworks may significantly improve segmentation precision. Integrating real-time data into clinical practice is a primary objective, facilitating prompt feedback for healthcare professionals. Ultimately, augmenting the system to automate the assessment of other fetal indicators, like femur length and belly circumference, would enhance its clinical use.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

The data that support the findings of this study are openly available in GitHub at https://github.com/pranjalrai-iitd/Fetal-head-segmentation-and-circumference-measurement-from-ultrasound-images.

Author Contribution Statement

Hamzah Jaber: Conceptualization, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing. **Ahmed Abed Mohammed:** Methodology, Validation, Formal analysis, Writing – review & editing. **Bo Zhang:** Software. **Maidi Qiu:** Software. **Mustafa M. Abd Zaid:** Validation, Project administration. **Putra Sumari:** Visualization, Supervision, Project administration.

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