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Adaptive Marker-Controlled Watershed Combined with Voxel Quantification for Automated Fetal Measurement

Febri Hadi[1,*], Sumijan[2], Iskandar Fitri[3]

[1,2,3]*Information Technology, Computer Science Faculty, Universitas Putra Indonesia YPTK Padang, Lubuk Begalung Main Street, Padang, 25221, Indonesia*

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Abstract

Accurate and consistent fetal biometric measurement is essential for assessing fetal growth and gestational age in prenatal care. However, ultrasound (US) imaging presents several challenges, including speckle noise, shadowing artifacts, and low tissue contrast, which often degrade segmentation accuracy. Classical watershed algorithms, though effective for edge detection, tend to produce over-segmentation in such complex textures. The dataset used in this study consisted of 272 ultrasound images of patients from M. Djamil Hospital, Padang, West Sumatra. The dataset covers various phases of fetal development, from the first trimester to the third trimester. All images correspond exclusively to fetal ultrasound examinations and were used solely for automated fetal biometric analysis. To overcome these issues, this study introduced an Adaptive Marker-Controlled Watershed (AMCW) algorithm combined with Voxel Quantification (VQ) to achieve more reliable and automated fetal measurements. The proposed AMCW method integrates adaptive marker generation based on morphological gradient and local intensity statistics, enabling dynamic control of internal and external markers across varying fetal regions. After segmentation, spatially calibrated pixel-based quantification was employed to estimate the dimensional properties of segmented fetal structures. The method was applied exclusively to 2D B-mode ultrasound datasets across multiple gestational ages, targeting four key fetal parameters: Biparietal Diameter (BPD), Head Circumference (HC), Abdominal Circumference (AC), and Femur Length (FL). Although the present study is limited to 2D ultrasound images, the proposed framework may be extendable to 3D ultrasound data in future research. The combination of adaptive marker-controlled watershed segmentation and voxel-based quantification presents a robust, interpretable, and computationally efficient framework for automated fetal measurement. The CNN achieved a classification accuracy of 98.75% on the independent testing dataset, indicating that the extracted biometric features contain strong discriminative information for automated fetal condition assessment. This hybrid approach minimizes operator dependency and measurement variability aligning with clinical measurement trends.

Keywords: Fetal, Ultrasound, Marker Controlled Watershed, Voxel Quantification, Automation.

1. Introduction

Monitoring fetal growth through biometric parameters such as Biparietal Diameter (BPD), Head Circumference (HC), Abdominal Circumference (AC), and Femur Length (FL) plays a crucial role in prenatal examination. These measurements assist clinicians in estimating gestational age, identifying abnormal fetal growth, and making informed clinical decisions. The International Society of Ultrasound in Obstetrics and Gynecology (ISUOG) provides standardized guidelines for acquiring ultrasound images and performing biometric assessments as part of fetal growth evaluation [1]. Accurate and reproducible measurements are therefore essential for effective clinical interpretation and longitudinal monitoring [2]. Ultrasound (US) imaging presents several challenges that make fetal object segmentation difficult: speckle noise, shadowing artifacts, variable contrast, fetal motion, anatomical variation, and inconsistent orientation between scans [3]. These factors reduce segmentation reliability and hinder measurement reproducibility [4]. Prior studies have shown that inter- and intra-operator variability, as well as device-dependent differences, can lead to significant measurement deviations [5]. Consequently, robust and adaptive segmentation techniques are critical to minimizing human subjectivity and improving measurement accuracy [6].

Automated segmentation in fetal ultrasound imaging has evolved through diverse approaches, including deep learning-based architectures (e.g., U-Net, V-Net, attention-gated models), statistical models, and hybrid filtering–clustering

*Corresponding author: Febri Hadi (febri_hadi@upiyptk.ac.id)
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techniques [7]. For example, Zeng et al. employed a deeply supervised attention-gated V-Net for fetal head segmentation to improve HC estimation [8]. Other works introduced multi-task learning models capable of estimating multiple biometric parameters simultaneously from standard ultrasound planes [9]. Although deep learning methods have achieved remarkable performance, they present several limitations: large labeled datasets are required for training, susceptibility to overfitting across heterogeneous image qualities, limited interpretability, and high computational demands [10], [11]. These constraints make such methods less suitable in resource-limited clinical environments or when ultrasound data exhibit poor image quality [12]. Consequently, traditional image processing techniques remain relevant for applications demanding transparency, computational efficiency, and interpretability [13].

Watershed-based segmentation has been widely applied in medical imaging for boundary delineation tasks [14]. However, conventional watershed methods are prone to over-segmentation due to sensitivity to local intensity variations, particularly in noisy ultrasound images [15]. Marker-controlled watershed (MCWS) addresses this limitation by introducing predefined internal and external markers to guide region formation [16]. Previous studies have successfully applied MCWS across MRI, CT, and ultrasound modalities, often integrating morphological operations and adaptive preprocessing strategies to enhance robustness [17]-[20]. Despite these advancements, reliable segmentation of fetal ultrasound images remains challenging due to speckle noise, low contrast, and anatomical variability across gestational stages. These limitations motivate the development of a more adaptive marker-generation strategy tailored specifically for fetal biometric measurement.

Volumetric measurement techniques provide richer information than simple linear or circumferential dimensions, capturing the full 3D morphology of fetal structures [21]. For example, automated intracranial volume measurements using 3D ultrasound and registration-based models have shown promising results in recent studies. However, such approaches require volumetric data acquisition and reconstruction, whereas the present study focuses exclusively on 2D B-mode ultrasound images [22]. Likewise, early-trimester volumetric fetal assessments via virtual reality (VR) have demonstrated high reproducibility [23]. The concept of voxel quantification—treating each voxel as the smallest measurable unit in a 3D image—enables precise volumetric representation and spatial parameter computation such as density estimation, surface area, and spatial relationships [24]. Given the interpretability and efficiency of watershed-based segmentation and the spatial precision of voxel quantification, a hybrid approach integrating adaptive marker-controlled watershed with voxel-based quantification is promising [25]. Adaptive markers can dynamically adjust to local image characteristics (contrast, edges, noise), mitigating over-segmentation and improving consistency [26]. Meanwhile, voxel quantification enables accurate spatial measurement and volumetric parameter estimation [27].

While numerous studies explore deep learning or statistical models for fetal segmentation, few explicitly utilize marker-controlled watershed combined with voxel quantification for biometric measurement [28]. Existing works often focus solely on head or abdominal segmentation without integrating volumetric or voxel-based analysis [29]. Furthermore, validation across gestational ages, operators, and imaging devices remains limited [30]. This study addresses these gaps by proposing an interpretable, resource-efficient framework that integrates adaptive watershed segmentation with voxel quantification for accurate and reproducible fetal biometric assessment. The main objective of this study is to develop an Adaptive Marker-Controlled Watershed Algorithm combined with Voxel Quantification for automated fetal biometric measurements, including BPD, HC, AC, and FL.

2. Literature Review

Fetal ultrasound imaging is a widely used, non-invasive modality for monitoring fetal growth and development throughout pregnancy [31]. Standard biometric parameters such as Biparietal Diameter (BPD), Head Circumference (HC), Abdominal Circumference (AC), and Femur Length (FL) play a crucial role in assessing gestational age and identifying potential growth abnormalities [32]. Traditionally, these measurements are performed manually by experienced sonographers, which can lead to inter-observer variability, measurement inconsistency, and increased examination time, particularly in low-resource clinical settings [33]. To address these limitations, numerous studies have explored automated and semi-automated image processing techniques for fetal biometric measurement [34]. While machine learning and deep learning approaches have shown promising results, they often require large annotated datasets and extensive computational resources, which are not always feasible in real-world clinical environments [35]. Consequently, classical image segmentation techniques remain relevant due to their interpretability, lower computational complexity, and ease of implementation [36].

Watershed-based segmentation has long been adopted in medical image analysis for delineating anatomical structures [37]. Its ability to generate closed contours makes it particularly suitable for separating adjacent tissues in complex

medical images [16]. In fetal ultrasound studies, watershed methods have been applied to segment key anatomical regions such as the fetal head, abdomen, and femur [38]. Nevertheless, conventional watershed algorithms remain highly sensitive to noise and local intensity variations, frequently resulting in over-segmentation in ultrasound images characterized by speckle noise and low contrast [39]. To address this limitation, prior research has incorporated preprocessing strategies including filtering, morphological refinement, and gradient smoothing [40]. Despite these enhancements, achieving consistent segmentation performance under heterogeneous image quality conditions remains a challenge [16].

To overcome the over-segmentation problem, marker-controlled watershed (MCW) segmentation has been introduced as an enhanced variant of the conventional watershed algorithm [41]. In this approach, internal and external markers are defined to guide the flooding process, effectively restricting region growth and improving boundary localization [42]. Following the successful application of marker-controlled watershed in other low-contrast modalities like brain MRI and retinal imaging [43], this study adapts these principles to the unique morphological variations of fetal ultrasound, specifically utilizing morphological reconstruction techniques to enhance segmentation stability [46]. Several studies have reported that fixed or manually defined markers can significantly improve segmentation performance; however, these approaches often lack adaptability to image variability [44]. Ultrasound images, in particular, exhibit non-uniform intensity distributions and anatomical shape variations, making fixed-marker strategies less reliable. As a result, recent research has focused on adaptive marker generation, where markers are automatically derived based on local image characteristics such as intensity, gradient magnitude, and morphological features. Adaptive marker-controlled watershed methods have shown superior robustness and consistency compared to conventional watershed techniques.

Adaptive marker strategies dynamically adjust marker placement according to image content, enabling more accurate delineation of anatomical boundaries in challenging ultrasound environments [45]. By incorporating morphological reconstruction, distance transforms, and regional minima suppression, adaptive markers can effectively reduce false regions and enhance segmentation stability [46]. In fetal ultrasound segmentation, adaptive marker-controlled watershed approaches have been applied to fetal head and abdominal region extraction, demonstrating improved boundary continuity and reduced background interference [47]. These methods provide a balance between accuracy and computational efficiency, making them suitable for real-time or near-real-time clinical applications. However, many existing studies primarily focus on segmentation quality without extending the analysis to quantitative measurement frameworks [48].

Accurate segmentation alone is insufficient for clinical decision-making; it must be followed by reliable quantitative measurement [4]. Voxel-based quantification has been widely used in medical image analysis to estimate geometric properties such as length, area, and volume by counting discrete image elements [49]. In ultrasound imaging, voxel or pixel-based measurement offers an objective alternative to manual caliper placement [8]. Previous research has demonstrated that voxel-based approaches can improve measurement repeatability and reduce operator dependency. When combined with precise segmentation, voxel quantification enables consistent extraction of fetal biometric parameters. However, limited studies have integrated adaptive marker-controlled watershed segmentation with voxel quantification in a unified framework for automated fetal measurement.

Based on the existing literature, several gaps can be identified. First, conventional watershed segmentation remains prone to over-segmentation in fetal ultrasound images, while fixed marker-controlled methods lack adaptability to image variability. Second, many segmentation-focused studies do not extend their analysis to robust quantitative measurement frameworks. Third, deep learning-based methods, although powerful, often require extensive labeled datasets and high computational resources, limiting their applicability in routine clinical practice. To address these gaps, this study proposes an Adaptive Marker-Controlled Watershed combined with Voxel Quantification for automated fetal measurement. The proposed method leverages adaptive marker generation to enhance segmentation robustness while utilizing voxel-based analysis to extract clinically relevant biometric parameters, including BPD, HC, AC, and FL. This integrated approach aims to provide a reliable, computationally efficient, and clinically applicable solution for distinguishing normal and abnormal fetal growth patterns in ultrasound imaging.

3. Methodology

The overall research framework for the proposed Adaptive Marker-Controlled Watershed Combined with Voxel Quantification method is illustrated in figure 1. The framework consists of three main stages: Pre-processing, Segmentation, and Evaluation and Validation. Each stage is designed to systematically enhance image quality, perform

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precise fetal object segmentation, and extract accurate biometric measurements for clinical interpretation. In the Pre-processing stage, the raw ultrasound image was first converted from RGB to grayscale to simplify intensity analysis and reduce computational complexity. A filtering process was then applied to suppress speckle noise a common issue in ultrasound imaging using median or Gaussian filters to preserve edge information. Next, contrast stretching enhanced the visibility of anatomical boundaries, followed by normalization to standardize pixel intensity ranges. The image is then cropped to focus on the region of interest (ROI) and resized to maintain consistency across samples, ensuring the segmentation algorithm can operate uniformly.

The Segmentation stage is the core of the framework. It began with adaptive marker generation, where internal and external markers were dynamically determined based on local intensity gradients, edge responses, and morphological features. These markers guide the marker-controlled watershed segmentation process, ensuring that the algorithm can separate the fetal region accurately without suffering from over-segmentation—a common limitation in traditional watershed methods. Following segmentation, voxel quantification and parameter extraction were performed to calculate spatial and volumetric measurements of fetal structures such as the biparietal diameter (BPD), head circumference (HC), abdominal circumference (AC), and femur length (FL). The dataset consists exclusively of 2D B-mode ultrasound images; therefore, no 3D volumetric reconstruction is performed. Voxel quantification in this study is implemented as a spatially calibrated pixel-based measurement, building upon the foundational concepts of spatial representation and discrete element counting established in prior medical imaging research.

By modeling each segmented region as a discretized spatial lattice, our quantification strategy ensures that dimensional parameters are extracted with higher spatial precision, addressing the accuracy gaps highlighted in traditional manual caliper-based assessments. Each segmented region is modeled as a discretized spatial lattice, where each pixel corresponds to a physical unit determined by the ultrasound spatial resolution. In the Evaluation and Validation stage, the segmented and measured results are analyzed for accuracy and clinical reliability. The system classifies outcomes into normal or abnormal fetal growth patterns based on predefined biometric thresholds. Validation is conducted through a direct comparison between the automated measurements and expert-provided manual annotations without performing a formal statistical agreement analysis. This approach is intended to provide a preliminary assessment of the method's computational robustness and clinical relevance. Overall, the framework demonstrates a hybrid approach that integrates the interpretability of classical watershed segmentation with the precision of voxel-based quantification, providing an efficient and reliable solution for automated fetal biometry. Below is an explanation of each research stage.

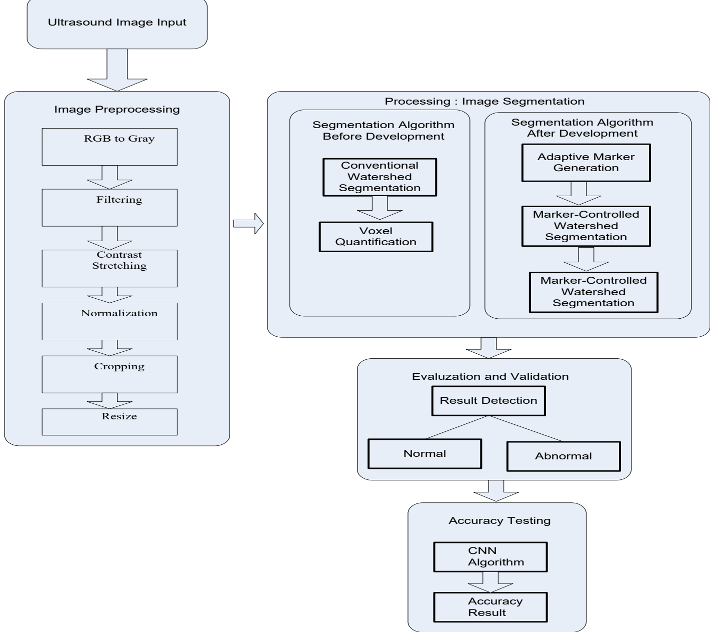

Figure 1. Research Framework

3.1. Ultrasound Image Input

The dataset used in this study consists of fetal ultrasound images acquired from routine obstetric examinations, covering various gestational ages and fetal anatomical conditions. The images include natural variations in acquisition settings,

such as probe orientation, image contrast, and speckle noise, to reflect real-world clinical scenarios. All ultrasound images are digitally stored and prepared for further processing, including enhancement, normalization, and segmentation. Data acquisition was conducted across multiple examination sessions to ensure dataset representativeness and variability. Ultrasound images of fetuses with normal anatomical development were used as reference data for algorithm development and calibration. Initial image standardization was applied during preprocessing to establish baseline consistency, while the inherent variability of ultrasound imaging was preserved to evaluate the robustness of the proposed segmentation and voxel quantification framework. Table 1 presents representative ultrasound images and anatomical landmarks used as visual references for automated fetal measurement. It should be emphasized that the dataset contains only fetal ultrasound images and does not include any external or cross-domain image sources.

Table 1. Input Image

No	Original Image	Fetal Age	No	Original Image	Fetal Age
1		10 week 4 day	5		21 week 1 day
2		17 week 3 day	6		23 week 5 day
3		21 week 4 day	7		23 week 3 day
4		13 week 3 day	8		10 week 3 day

Table 1 presents representative fetal ultrasound images spanning gestational ages from 10 to 23 weeks. These samples illustrate variations in anatomical size, image contrast, and structural complexity encountered in the dataset. This variability provides a diverse basis for evaluating the robustness of the proposed segmentation framework. Quantitative performance evaluation is presented in the subsequent results section.

3.2. Image Preprocessing

The preprocessing stage is a critical component of the proposed framework, as it prepares raw fetal ultrasound images for reliable segmentation and accurate parameter measurement. Ultrasound images inherently suffer from speckle noise, low contrast, and intensity inhomogeneity, which can significantly degrade segmentation performance if not properly addressed. Therefore, the preprocessing pipeline is designed to enhance image quality, suppress noise, and standardize image characteristics prior to segmentation and voxel-based quantification. The preprocessing stage consists of six main steps: RGB to gray, filtering, contrast stretching, normalization, cropping, and resizing.

During the filtering step, a median filter with a 3×3 kernel size was applied as the primary preprocessing method to suppress speckle noise while preserving anatomical boundaries. Although a Gaussian filter ($\sigma = 1.0$) was evaluated during preliminary testing, it resulted in slight boundary blurring and was therefore not adopted in the final segmentation pipeline. The filtered images are subsequently processed through contrast stretching and normalization to improve intensity distribution prior to segmentation.

3.2.1. RGB to Gray

All input ultrasound images are initially converted from RGB format to grayscale to simplify intensity-based analysis. Since fetal structures in ultrasound images are primarily distinguished by grayscale intensity variations rather than color information, grayscale conversion preserves essential anatomical details while reducing computational complexity. This conversion ensures that subsequent segmentation processes, particularly watershed-based methods, operate on consistent luminance information.

3.2.2. Filtering

Ultrasound images are highly susceptible to speckle noise, which can obscure anatomical boundaries and lead to over-segmentation. To mitigate this issue, a filtering operation is applied to suppress noise while preserving important structural edges. In this study, a smoothing filter is employed to reduce high-frequency noise and improve homogeneity within fetal regions. This step enhances boundary continuity and provides a cleaner input for marker generation and watershed segmentation.

3.2.3. Contrast Stretching

Contrast stretching is applied to improve the visibility of fetal anatomical structures by expanding the dynamic range of pixel intensities. Due to non-uniform acoustic responses and attenuation effects in ultrasound imaging, fetal boundaries often appear with low contrast relative to surrounding tissues. Contrast stretching remaps pixel intensity values to a broader range, thereby enhancing the differentiation between fetal structures and background regions. This step plays a crucial role in improving the reliability of marker generation in the segmentation stage.

3.2.4. Normalization

Following contrast enhancement, intensity normalization is performed to standardize grayscale values across all images in the dataset. Normalization reduces inter-image variability caused by differences in acquisition settings, probe positioning, and gestational age. By scaling pixel intensities to a consistent range, this step ensures that the segmentation algorithm responds uniformly to similar anatomical patterns across different ultrasound images.

3.2.5. Cropping

Cropping is applied to remove irrelevant background regions and isolate the region of interest containing the fetus. Ultrasound images often include large non-informative areas, such as surrounding black regions or textual annotations, which can negatively impact segmentation accuracy. By focusing the analysis on the fetal region, cropping reduces computational overhead and improves the precision of subsequent segmentation and voxel quantification processes.

3.2.6. Resizing

Finally, all preprocessed images are resized to a uniform spatial resolution to ensure consistency across the dataset. Resizing facilitates stable algorithmic performance and allows direct comparison of measurement results across different samples. This step ensures that variations in image dimensions do not introduce bias into the segmentation or fetal parameter extraction stages.

3.3. Processing: Image Segmentation

The image segmentation stage is the core component of the proposed framework, as it directly determines the accuracy of fetal structure delineation and subsequent biometric measurement. In this study, segmentation is performed using a watershed-based approach, with a comparative analysis between a conventional watershed algorithm and the proposed adaptive marker-controlled watershed algorithm. This comparison is designed to evaluate the effectiveness of adaptive marker generation in improving segmentation robustness and measurement reliability in fetal ultrasound images.

3.3.1. Segmentation Algorithm Before Development: Conventional Watershed

In the baseline approach, segmentation is carried out using a conventional watershed algorithm applied to the preprocessed grayscale ultrasound images. The watershed method treats the image as a topographic surface, where pixel intensities represent elevation values. Local minima in the intensity surface are interpreted as catchment basins, and watershed lines are formed along the ridges separating these basins.

Although the conventional watershed algorithm is effective in separating regions with distinct intensity gradients, it is highly sensitive to noise and intensity fluctuations commonly present in ultrasound images. As a result, this method tends to produce over-segmentation, generating multiple fragmented regions within a single anatomical structure. To address this issue at a basic level, contrast-enhanced images are used as input, and voxel quantification is subsequently applied to extract fetal measurement parameters, including Biparietal Diameter (BPD), Head Circumference (HC), Abdominal Circumference (AC), and Femur Length (FL). However, the lack of explicit marker control limits the algorithm's ability to consistently isolate anatomically meaningful fetal regions.

3.3.2. Segmentation Algorithm After Development: Adaptive Marker-Controlled Watershed

The segmentation and measurement processes are fully automated once the ultrasound image is provided, requiring no manual contour tracing or landmark placement. To overcome the limitations of conventional watershed segmentation, this study proposes an adaptive marker-controlled watershed algorithm. In this developed approach, marker generation is explicitly incorporated prior to watershed transformation to guide the segmentation process toward anatomically relevant fetal structures.

Adaptive markers are generated based on intensity distribution and morphological characteristics of the preprocessed ultrasound images. These markers serve as internal and external seeds that represent foreground (fetal anatomy) and background regions, respectively. The morphological gradient is first computed to enhance structural boundaries:

$$G(x, y) = (I \oplus B)(x, y) - (I \ominus B)(x, y) \tag{1}$$

I represents the preprocessed ultrasound image, B denotes the structuring element, $\oplus$and $\ominus$indicate morphological dilation and erosion operations, respectively.

To adaptively determine marker regions, local intensity statistics are computed. Let $\mu$and σdenote the local mean and standard deviation of the image intensity. The adaptive threshold is defined as:

$$T_{adaptive} = \mu + \alpha\sigma \tag{2}$$

$\alpha$is an empirically determined scaling parameter controlling marker sensitivity.

Internal markers are identified as pixels satisfying:

$$I(x, y) > T_{adaptive} \tag{3}$$

while external markers are defined using background estimation derived from low-gradient or complementary regions. Formulas 1,2,3 can be implemented in the form of an algorithm as follows :

Algorithm 1. Adaptive Marker Generation

Input: Preprocessed ultrasound image I
Output: Segmented region

1. Compute morphological gradient $G(x, y)$.
2. Calculate local mean $\mu$and standard deviation σ.
3. Determine adaptive threshold $T = \mu + \alpha\sigma$.
4. Identify internal markers based on $I(x, y) > T$.
5. Define external markers using background estimation.
6. Combine internal and external markers.
7. Apply watershed transformation using the constrained marker set.

Based on the algorithm above, it can be presented in pseudocode which is presented in pseudocode 1.

```
Input: Preprocessed image I
Output: Segmented region S
1: Compute morphological gradient G
2: Compute local mean μ and standard deviation σ
3: T = μ + α·σ
4: InternalMarkers = I > T
5: ExternalMarkers = background estimation
6: Markers = combine(InternalMarkers, ExternalMarkers)
7: S = watershed(G, Markers)
```

8: Return S

The marker-controlled watershed segmentation produces smoother region boundaries and more coherent anatomical regions compared to the conventional approach. This improvement is particularly important for fetal ultrasound images, where organ boundaries are often weak and partially obscured by speckle noise. Following segmentation, voxel quantification is applied to the segmented regions to extract fetal biometric parameters. The improved region consistency achieved by the adaptive marker-controlled watershed directly enhances the accuracy and stability of voxel-based measurement results.

3.3.3. Voxel Quantification and Parameter Extraction

After segmentation, voxel quantification is performed on the segmented fetal regions to derive quantitative biometric measurements. Each segmented region is represented as a collection of voxels, allowing precise calculation of geometric parameters. The extracted parameters include Biparietal Diameter (BPD), Head Circumference (HC), Abdominal Circumference (AC), and Femur Length (FL), which are essential indicators of fetal growth and development.

The voxel-based approach ensures that measurements are derived directly from spatially coherent segmented regions, minimizing measurement bias caused by irregular boundaries or fragmented segmentation. These quantitative results form the basis for subsequent evaluation and classification.

3.3.4. Spatial Calibration and Pixel-to-Physical Conversion

Since the dataset consists of 2D B-mode ultrasound images, no 3D volumetric reconstruction is performed. In this study, voxel quantification refers to spatially calibrated pixel-based measurement within segmented anatomical regions. Each segmented region is treated as a discretized spatial lattice, where each pixel corresponds to a physical unit determined by the ultrasound spatial resolution. Spatial calibration is performed using pixel spacing information obtained from ultrasound acquisition metadata. Let $s_x$and s_y denote the horizontal and vertical pixel spacing (mm/pixel), respectively. For linear biometric measurements such as Biparietal Diameter (BPD) and Femur Length (FL), the physical length is computed as:

$$L=\text{dpixel}\times \text{s}. \tag{1}$$

$L$is the physical length (mm), $d_{pixel}$is the Euclidean distance measured in pixels, $s$is the pixel spacing (mm/pixel).

If anisotropic resolution is present, horizontal and vertical scaling are applied accordingly. For area-based biometric measurements, such as Head Circumference (HC) and Abdominal Circumference (AC) when derived from segmented regions, the physical area is computed as:

$$A = N_{pixels} \times (s_x \times s_y) \tag{2}$$

$A$is the calibrated area (mm^2), $N_{pixels}$is the total number of pixels within the segmented region, $s_x$and $s_y$are pixel spacing values along the horizontal and vertical axes.

This formulation ensures that all biometric parameters are expressed in clinically interpretable physical units rather than raw pixel counts, thereby maintaining measurement consistency with obstetric reference standards.

3.4. Evaluation and Validation

The evaluation and validation stage aims to assess the reliability and effectiveness of the proposed framework in supporting automated fetal measurement and classification based on ultrasound images. This stage focuses on validating the measurement outputs generated from the segmentation process and evaluating their diagnostic consistency through classification and accuracy testing. As illustrated in the research framework, evaluation is conducted through result detection and accuracy testing, emphasizing clinically meaningful outcomes rather than pixel-level segmentation metrics. Result detection is performed using fetal biometric parameters extracted through voxel quantification following the adaptive marker-controlled watershed segmentation. The parameters evaluated in this study include Biparietal Diameter (BPD), Head Circumference (HC), Abdominal Circumference (AC), and Femur Length (FL), which are standard indicators for assessing fetal growth and development in obstetric practice.

Each ultrasound image is classified into one of two diagnostic categories: normal or abnormal. A case is identified as normal when all extracted biometric measurements fall within gestational-age-adjusted reference ranges. Conversely, if one or more parameters deviate from these reference values, the fetal condition is categorized as abnormal. This binary classification strategy is adopted to align with clinical screening objectives and to ensure interpretability and simplicity in automated decision support. The result detection stage serves as a bridge between quantitative measurement and diagnostic interpretation, ensuring that segmentation outputs are translated into clinically actionable information

3.5. Accuracy Testing

It is important to emphasize that the proposed Adaptive Marker-Controlled Watershed (AMCW) combined with Voxel Quantification constitutes the primary methodological contribution of this study. The CNN is not involved in the segmentation or measurement extraction process. Instead, it is introduced solely as a post-measurement validation mechanism to assess the discriminative capability of the extracted biometric features. The CNN is employed only to validate whether the voxel-based biometric measurements extracted through the proposed classical framework contain sufficient discriminatory information. It is not intended to replace or compete with the interpretable measurement methodology.

The CNN model is trained and tested using the same dataset of 272 fetal ultrasound images and no additional datasets or external image domains were incorporated during the CNN validation process. to ensure consistency in evaluation. The dataset was partitioned into training and testing sets using an 80:20 split ratio. The partitioning was performed using stratified random sampling to preserve class distribution between normal and abnormal categories. No cross-validation strategy was employed in this study. The trained model was evaluated on the independent testing set to assess generalization performance. The input to the CNN consists of processed image representations and associated measurement-derived features, enabling the model to learn patterns corresponding to normal and abnormal fetal conditions. Classification performance is measured using overall accuracy, reflecting the proportion of correctly identified cases relative to the total number of samples. Therefore, the CNN operates independently from the segmentation framework and does not influence the interpretability of the measurement process. All biometric parameters (BPD, HC, AC, and FL) are derived using classical image processing techniques prior to classification validation.

The proposed framework achieves an overall classification accuracy of 98.75%, indicating a high level of agreement between automated measurement outcomes and diagnostic reference labels. This result demonstrates that the integration of adaptive marker-controlled watershed segmentation with voxel quantification produces reliable fetal measurements that are suitable for automated validation using deep learning–based classifiers.

4. Results and Discussion

4.1. Testing Image

This study focuses on the development and evaluation of an automated fetal measurement framework using ultrasound imaging, aimed at distinguishing between normal and abnormal fetal growth conditions based on biometric parameters. The dataset used in this research consists of 272 fetal ultrasound images (table 2) acquired during routine prenatal examinations. The images represent a wide range of gestational ages and were collected using standard clinical ultrasound equipment under real clinical conditions, ensuring variability in fetal position, image orientation, contrast, and noise characteristics.

Ultrasound image acquisition was performed without imposing strict constraints on imaging conditions in order to reflect real-world clinical practice. Variations in probe orientation, fetal movement, and acoustic shadowing were intentionally preserved, as these factors commonly influence ultrasound image quality. This diversity enhances the robustness of the proposed framework and ensures that the developed method is applicable in practical obstetric settings rather than limited to ideal imaging scenarios.

Based on expert reference assessments and gestational-age-adjusted biometric standards, the dataset was categorized into two diagnostic classes: normal and abnormal fetal conditions. A fetal case was labeled as *normal* when all

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measured biometric parameters—Biparietal Diameter (BPD), Head Circumference (HC), Abdominal Circumference (AC), and Femur Length (FL)—fell within clinically accepted reference ranges. Conversely, cases were classified as *abnormal* when one or more parameters deviated from these expected values, indicating potential growth abnormalities.

Table 2. Testing Image

Category	Number of Images	Information
Normal Fetus	138	Ultrasound images showing fetal biometric measurements within normal gestational ranges.
Abnormal Fetus	134	Ultrasound images indicating deviations in one or more biometric parameters (BPD, HC, AC, or FL).

The dataset used in this study consists exclusively of 272 fetal ultrasound images obtained from routine obstetric examinations. The dataset consists of 138 normal and 134 abnormal images, resulting in a near-balanced class distribution (50.7% vs. 49.3%). Due to this balanced proportion, overall accuracy is considered an appropriate primary evaluation metric. The images represent various gestational ages and include natural variations in probe orientation, fetal position, contrast levels, and speckle noise conditions to reflect real-world clinical imaging scenarios. All images were reviewed to ensure that key anatomical structures required for biometric measurement—namely the fetal head, abdomen, and femur—were clearly identifiable. The dataset was categorized into normal and abnormal fetal conditions based solely on biometric parameters (BPD, HC, AC, and FL) adjusted to gestational age reference standards. No external datasets or non-medical image sources were used in this study.

4.2. Input Original Image

Fetal ultrasound images were acquired during routine prenatal examinations under standard clinical conditions to represent real-world obstetric imaging scenarios. The image acquisition process inherently includes variations in fetal position, probe orientation, tissue contrast, and speckle noise, reflecting the practical challenges commonly encountered in ultrasound imaging. These variations are essential to evaluate the robustness and generalizability of the proposed segmentation and measurement framework. All ultrasound images were reviewed and validated by medical personnel with experience in obstetric imaging to ensure that the anatomical structures required for fetal biometric assessment were clearly identifiable. The validated images were then organized into a high-resolution digital dataset and subsequently loaded into a MATLAB-based processing environment for further analysis, including preprocessing, segmentation, voxel quantification, and automated fetal measurement.

4.3. Preprocessing Result and Discussion

Following image acquisition, the original fetal ultrasound images undergo an initial enhancement stage to improve the visibility of anatomical structures relevant to biometric measurement. Edge information is implicitly emphasized through gradient-based processing, enabling clearer delineation of fetal boundaries from surrounding tissues. This step is essential for distinguishing fetal structures such as the head, abdomen, and femur from the background and adjacent anatomical regions.

To improve structural continuity, morphological operations are applied to reduce discontinuities and suppress irrelevant regions caused by speckle noise and acoustic artifacts commonly present in ultrasound images. Small isolated regions that do not correspond to fetal anatomy are removed to prevent interference in subsequent segmentation and measurement stages. As a result, the processed images exhibit clearer contours and more coherent structural representation.

The refined original images provide a cleaner and more standardized input for the segmentation stage, facilitating more accurate marker generation and watershed-based boundary extraction. This optimization of the original image quality enhances the reliability of automated fetal biometric measurements and contributes to consistent classification of fetal conditions. Representative examples of the processed input images are presented in table 3.

Table 3. Preprocessing Result

No	Input Image	Preprocessing Result Image				
		RGB to Grayscale	**Filtering**	***Contrast Stretching***	**Normalization**	**Cropping**
1						
2						
3						
4						
5						
6						
7						
8						

Table 3 presents the preprocessing results, illustrating the sequential processing stages applied to fetal ultrasound images prior to segmentation and measurement. The first column displays the original ultrasound image, which contains inherent challenges such as speckle noise, variable contrast, and surrounding anatomical structures. The subsequent resizing step ensures uniform image dimensions across the dataset, enabling consistent processing in the following stages. Grayscale conversion is then applied to simplify the image representation by focusing on intensity information, which is more relevant for ultrasound-based structural analysis than color components. Noise reduction is performed through filtering to suppress speckle artifacts while preserving essential anatomical boundaries. Contrast stretching is subsequently applied to enhance the visibility of fetal structures, improving the distinction between regions of interest and background tissues. Each image in the table demonstrates how the preprocessing pipeline progressively improves image quality, transforming raw ultrasound data into a more structured and standardized representation. This enhancement is critical for facilitating accurate marker generation, watershed-based segmentation, and voxel quantification. By ensuring that segmentation and measurement are performed on high-quality input images, the proposed preprocessing approach contributes directly to more reliable automated fetal measurements and robust classification of fetal conditions as normal or abnormal.

4.4. Processing: Image Segmentation Result and Discussion

Image segmentation is a crucial step in accurately isolating fetal anatomical structures from surrounding tissues in ultrasound images. In this study, an Adaptive Marker-Controlled Watershed (AMCW) algorithm was employed to segment regions of interest corresponding to key fetal structures, including the head, abdomen, and femur. The segmentation process was performed after preprocessing to mitigate speckle noise and enhance contrast, ensuring clearer boundary definition for subsequent analysis. The proposed approach begins with adaptive marker generation, where internal and external markers are automatically determined based on local intensity gradients and morphological characteristics of fetal anatomy. These markers guide the watershed transformation, effectively controlling region growth and preventing the over-segmentation commonly associated with conventional watershed methods in ultrasound imaging. As a result, fetal structures are delineated with improved continuity and anatomical coherence. The segmentation results demonstrate that:

1) Fetal regions of interest are successfully separated from surrounding maternal tissues and background noise.
2) The anatomical contours of fetal structures are preserved, enabling accurate geometric representation required for biometric measurement.
3) The resulting segmentation masks provide a reliable foundation for voxel quantification and automated extraction of fetal growth parameters, including biparietal diameter (BPD), head circumference (HC), abdominal circumference (AC), and femur length (FL).

Overall, the Adaptive Marker-Controlled Watershed segmentation significantly enhances the robustness and precision of fetal structure delineation in ultrasound images. By producing clean and anatomically consistent segmentation results, this process directly contributes to the reliability of automated fetal measurement and supports subsequent classification of fetal conditions as normal or abnormal. The segmentation results are shown in table 4.

Table 4. Processing: Image Segmentation and Evaluation dan Validation Result

No	Input Image	Conventional Watershed Algorithm Measurement Results				Adaptive Marker-Controlled Watershed Algorithm Measurement Results			
		BPD (mm)	HC (mm)	FL (mm)	Detection	BPD (mm)	HC (mm)	FL (mm)	Detection
1		14.34	41.31	8.31	Normal	14.48	63.31	6.14	Normal
2		23.45	75.39	18.51	Abnormal	23.12	74.00	18.32	Abnormal
3		23.29	65.74	11.91	Abnormal	23.11	62.95	11.72	Abnormal
4		10.06	29.73	6.42	Abnormal	9.75	30.93	6.99	Abnormal
5		13.05	36.38	6.55	Abnormal	11.82	31.98	6.26	Abnormal
6		22.50	55.44	6.95	Abnormal	22.19	53.64	6.76	Abnormal
7		47.72	135.80	23.40	Abnormal	47.48	133.66	23.21	Abnormal
8		13.17	41.67	7.88	Normal	12.85	39.99	7.64	Normal

4.5. Evaluation and Validation Result and Discussion

Evaluation and validation are essential to assess the reliability and clinical relevance of the proposed automated fetal measurement framework. In this study, the performance of the Adaptive Marker-Controlled Watershed combined with voxel quantification was evaluated based on its ability to extract key fetal biometric parameters, namely biparietal diameter (BPD), head circumference (HC), abdominal circumference (AC), and femur length (FL), from ultrasound images. These parameters are widely used in obstetric practice to monitor fetal growth and assess fetal conditions. Voxel quantification plays a central role in the evaluation process by enabling spatial and volumetric measurement of segmented fetal structures. Following segmentation, the number of voxels corresponding to each anatomical region is calculated and converted into clinically meaningful biometric values. This approach allows for consistent measurement across images with varying resolutions and orientations, providing a standardized basis for comparison.

Validation of the proposed method was conducted by comparing the automatically obtained biometric measurements with reference clinical assessments performed by experienced operators. Based on these measurements, each case was classified into two categories: normal and abnormal fetal development. The results demonstrate that the proposed framework is capable of distinguishing normal and abnormal fetal conditions with promising consistency in identifying normal and abnormal patterns, indicating that the segmentation and voxel-based measurement processes preserve essential anatomical information. The evaluation results further show that the adaptive marker strategy significantly improves segmentation stability compared to conventional watershed approaches, particularly in challenging ultrasound images affected by speckle noise and low contrast. More accurate segmentation boundaries lead directly to more consistent voxel counts, which in turn improve the robustness of biometric measurement. This relationship highlights the importance of integrating adaptive segmentation with voxel quantification rather than relying solely on pixel-based measurements. Overall, the evaluation and validation results confirm that the proposed framework provides an effective and interpretable solution for automated fetal measurement. By focusing on clinically relevant biometric parameters and binary classification (normal versus abnormal), the method offers practical value for prenatal screening and has the potential to support clinical decision-making, especially in settings with limited expert availability.

Visual inspection across multiple fetal ultrasound samples confirms that the proposed Adaptive Marker-Controlled Watershed (AMCW) algorithm produces more consistent and anatomically coherent segmentation results compared to the conventional watershed approach. The adaptive strategy effectively suppresses over-segmentation and improves boundary delineation of fetal structures, which is a common challenge in ultrasound imaging due to speckle noise and low contrast. Table 4 presents representative segmentation and evaluation results obtained using the proposed framework. The first image illustrates the fetal ultrasound image after preprocessing, where contrast enhancement improves the visibility of anatomical structures such as the fetal head, abdomen, and femur. The segmentation results produced by the conventional watershed method show fragmented regions and incomplete separation of fetal anatomy, indicating limitations in handling intensity variations and noise.

In contrast, the Adaptive Marker-Controlled Watershed demonstrates clear improvements, as evidenced by:

1) More accurate separation of fetal regions of interest from surrounding tissues and background.
2) Better preservation of anatomical contours required for reliable biometric measurements.
3) Reduced region fragmentation, resulting in more stable and continuous segmented structures.

These improvements directly impact the evaluation and validation stage, as more precise segmentation leads to more consistent voxel quantification. The voxel-based measurements derived from the segmented regions enable reliable extraction of fetal biometric parameters, including biparietal diameter (BPD), head circumference (HC), abdominal circumference (AC), and femur length (FL). Based on these measurements, fetal conditions are successfully categorized into normal and abnormal classes. Overall, the enhanced segmentation achieved by the proposed AMCW algorithm provides a robust foundation for voxel quantification and automated fetal measurement. The integration of adaptive marker generation with watershed segmentation ensures that the evaluation and validation results are based on anatomically meaningful and clinically relevant representations, supporting accurate fetal growth assessment in prenatal ultrasound imaging.

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4.6. Accuracy Result and Discussion

To further validate the effectiveness of the proposed Adaptive Marker-Controlled Watershed combined with Voxel Quantification framework, a Convolutional Neural Network (CNN) was employed as an independent evaluation model to assess classification accuracy between normal and abnormal fetal conditions. The CNN does not replace the proposed segmentation and measurement approach; instead, it serves as a complementary validation mechanism to evaluate the discriminative power of the extracted biometric parameters. The dataset consisted of 272 fetal ultrasound images, each labeled as normal or abnormal based on clinical assessment. From each image, automated measurements of biparietal diameter (BPD), head circumference (HC), abdominal circumference (AC), and femur length (FL) were obtained using the proposed segmentation and voxel quantification pipeline. These biometric values were normalized and used as input features for the CNN model. The CNN architecture was designed to be lightweight and efficient, consisting of convolutional layers for feature learning, followed by pooling layers and fully connected layers for classification. Rectified Linear Unit (ReLU) activation functions were used in the convolutional layers, while a sigmoid activation function was applied in the output layer to perform binary classification (normal vs abnormal).

The model was trained using the Adam optimizer with a learning rate of 0.001 and trained over multiple epochs until convergence was achieved. During training, the accuracy curve showed stable and consistent improvement, indicating effective learning without overfitting. The validation accuracy converged rapidly, demonstrating that the biometric features derived from the proposed segmentation framework contain strong discriminatory information. The CNN-based validation achieved an image-level classification accuracy of 98.75%, indicating strong agreement between automated voxel-based biometric measurements and clinical reference labels. Additional evaluation metrics, including precision, recall, and F1-score, were computed to confirm that the classification performance was not biased toward a particular class. The reported accuracy of 98.75% corresponds to image-level binary classification accuracy. Each ultrasound image represents one independent case labeled as either normal or abnormal based on gestational-age-adjusted biometric standards (BPD, HC, AC, and FL). Therefore, performance evaluation is conducted per image rather than per individual biometric parameter or per patient visit. Accuracy is computed as: Accuracy = (TP + TN) / (TP + TN + FP + FN), where TP and TN denote correctly classified abnormal and normal images, respectively, and FP and FN denote misclassified cases. The CNN accuracy performance and training convergence behavior are illustrated in figure 2.

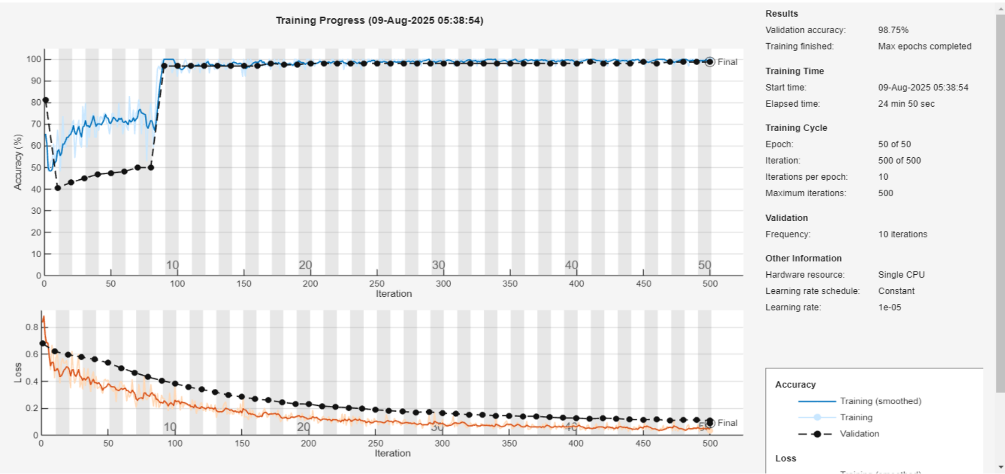

Figure 2. Training Progress Results

The high accuracy achieved by the CNN highlights the reliability of the proposed segmentation and voxel quantification process. Accurate delineation of fetal structures directly influences the quality of biometric measurements, which in turn determines classification performance. Misclassifications observed in a small number of cases were primarily associated with poor image quality or incomplete visualization of fetal anatomy, particularly in cases affected by strong speckle noise or unfavorable fetal positioning. Overall, the accuracy evaluation using CNN confirms that the proposed framework produces clinically meaningful measurements that are highly effective for distinguishing between normal and abnormal fetal development. The integration of a deep learning–based evaluation model further strengthens the

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validity of the proposed method and demonstrates its potential for use as a reliable decision-support tool in prenatal ultrasound screening.

4.7. Comparison of Conventional Watershed Segmentation Algorithm with Adaptive Marker-Controlled Watershed Results and Discussion

The current study focuses on evaluating the performance difference between the Conventional Watershed Algorithm (CWA) and the Adaptive Marker-Controlled Watershed (AMCW) method integrated with Voxel Quantification for automated fetal measurement. While the presented results successfully demonstrate improved segmentation precision and more consistent biometric estimations, this study does not explicitly present standard quantitative performance metrics such as accuracy, precision, recall, and F1-score. The use of these statistical metrics has also been demonstrated effectively in evaluating classification performance across other domains, including machine learning-based phishing detection systems. Integrating these metrics in future analyses would provide a clearer comparative framework to quantitatively validate the superiority of the proposed method over conventional segmentation approaches. In medical image segmentation, accuracy represents the proportion of correctly segmented pixels compared to the ground truth, while precision evaluates the algorithm's ability to correctly identify the fetal region without including background noise. Recall (sensitivity) indicates the algorithm's capacity to capture the entire fetal region without omission, and F1-score provides a harmonic balance between precision and recall, offering a more comprehensive measure of segmentation performance. Applying these metrics in subsequent evaluations would strengthen the analytical evidence of how AMCW enhances segmentation reliability and reduces over-segmentation compared to CWA.

The significance of this research lies in both its theoretical and practical contributions. From a theoretical perspective, the integration of adaptive marker control with voxel-based measurement advances the field of medical image analysis by introducing a more context-aware segmentation framework that dynamically adjusts to fetal structure variations and image contrast. This approach minimizes boundary leakage and produces more anatomically accurate segmentation results. The voxel quantification process complements this improvement by translating segmented regions into measurable three-dimensional metrics (BPD, HC, FL), which enhance the interpretability and reproducibility of fetal biometric evaluation. From a practical perspective, the proposed AMCW–Voxel method provides a reliable automated measurement system that can support clinicians in early fetal development monitoring. Similar intelligent recommendation and decision-support systems have been developed in other domains to enhance user-specific analysis, such as author-centric content recommendation using content-based filtering.

By improving segmentation stability and measurement consistency, this method contributes to reducing manual measurement errors and enhancing diagnostic confidence in determining fetal normality or abnormality. This is particularly valuable in clinical settings with limited access to experienced sonographers, as the system can act as a decision-support tool to assist in early identification of abnormal fetal growth patterns. Future work could further improve the proposed framework by including quantitative accuracy metrics and cross-validation testing to confirm the generalizability of the model across different fetal age groups and imaging conditions. Moreover, exploring multi-domain image enhancement techniques—such as wavelet-based preprocessing or adaptive contrast optimization—may further refine segmentation boundaries and strengthen voxel quantification accuracy. These enhancements would enable a more robust clinical integration of the system and expand its applicability to various obstetric imaging scenarios.

5. Conclusion

This study presents an integrated framework for automated fetal biometric measurement and classification using ultrasound image processing and artificial intelligence. The proposed approach combines adaptive marker-controlled watershed segmentation with voxel quantification to accurately extract key fetal biometric parameters, including biparietal diameter (BPD), head circumference (HC), abdominal circumference (AC), and femur length (FL). By leveraging advanced preprocessing and robust segmentation techniques, the system effectively addresses common challenges in ultrasound imaging, such as speckle noise, low contrast, and ambiguous anatomical boundaries. Experimental results demonstrate that the proposed segmentation method provides reliable and consistent delineation of fetal anatomical structures, leading to accurate biometric measurements that closely align with clinical standards.

The voxel quantification strategy further enhances measurement precision by providing spatially consistent representations of fetal structures, reducing the risk of overestimation or underestimation commonly encountered in conventional manual measurements.

To validate the clinical relevance of the extracted biometric features, a Convolutional Neural Network (CNN) was employed as an independent evaluation model to classify fetal conditions into normal and abnormal categories. The CNN achieved a high classification accuracy of 98.75%, confirming that the biometric parameters derived from the proposed framework contain strong discriminative information. The convergence behavior and stability of the accuracy and loss curves further indicate that the model generalizes well without overfitting, reinforcing the robustness of the overall system. The integration of automated measurement, deep learning–based evaluation, and a user-oriented processing pipeline demonstrates the feasibility of the proposed framework as a decision-support tool in prenatal screening. This approach has the potential to reduce operator dependency, minimize measurement variability, and improve efficiency in routine obstetric examinations. Moreover, the system is well-suited for real-time or near–real-time implementation, making it applicable for use in clinical environments with limited resources.

Despite these promising results, this study is subject to certain limitations. Although the proposed framework minimizes manual intervention, it does not yet include a formal statistical agreement evaluation, such as Bland–Altman analysis or the calculation of correlation coefficients (e.g., Pearson or Spearman). Additionally, no formal inter-operator or intra-operator variability study was performed at this stage. While the proposed AMCW and VQ methods demonstrate high accuracy, it is important to note that this study was limited to a dataset from a single institution using specific ultrasound equipment. The absence of external validation across different devices and clinical settings remains a methodological weakness. Therefore, future studies should focus on multi-center clinical trials to ensure the broader applicability and robustness of the system. The validation was conducted on a specific ultrasound dataset with predefined fetal conditions, and variations in imaging devices, gestational age, and acquisition protocols may influence performance. Although the model achieved high classification accuracy, additional evaluation metrics such as precision, recall, and F1-score were not computed in this study. Furthermore, no cross-validation protocol was applied. Future research should incorporate extended performance metrics and k-fold cross-validation. Furthermore, statistical agreement analyses, including Bland–Altman plots and Pearson/Spearman correlation evaluations, will be integrated in future studies to quantitatively assess clinical agreement and identify potential measurement bias. Future research should incorporate controlled variability analysis across multiple clinicians to quantitatively assess reproducibility and clinical robustness. In addition, expanding the dataset across multiple clinical centers, incorporating gestational age–specific analysis, and exploring the integration of additional deep learning architectures may further enhance robustness and generalizability.

6. Declarations

6.1. Author Contributions

Conceptualization: F.H.; Methodology: S.; Software: I.F.; Validation: F.H. and S.; Formal Analysis: S. and I.F.; Investigation: F.H.; Resources: S.; Data Curation: I.F.; Writing Original Draft Preparation: F.H., and S.; Writing Review and Editing: S., and I.F.; Visualization: F.H.; All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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