Fetal Biometry: Detection of Biparietal Diameter and Occipitofrontal Landmark Points in Axial Images using YOLOv5 Algorithm

Keywords: Biparietal Diameter, Occipitofrontal, Fetal Biometry, YOLOv5

Abstract. This work presents an approach for the automated detection of biparietal diameter (BPD) and occipitofrontal (OF) landmark points in fetal axial images using the YOLOv5 algorithm. Accurate measurement of fetal biometry is crucial for monitoring prenatal development and assessing overall health. The proposed algorithm leverages the YOLOv5 architecture, known for its efficiency and accuracy in object detection tasks. My methodology involves preprocessing a comprehensive dataset of fetal axial images. The images are preprocessed to ensure consistent quality, and a YOLOv5 model is trained to predict the coordinates of BPD and OF landmark points. The model is fine-tuned to optimize performance and rigorous evaluation metrics. Just 50 epochs are run and get an mAP score of 0.407 for the value of the IOU score of 0.50. Also, recall and precision are 0.464 and 0.478 respectively.

1 Motivation

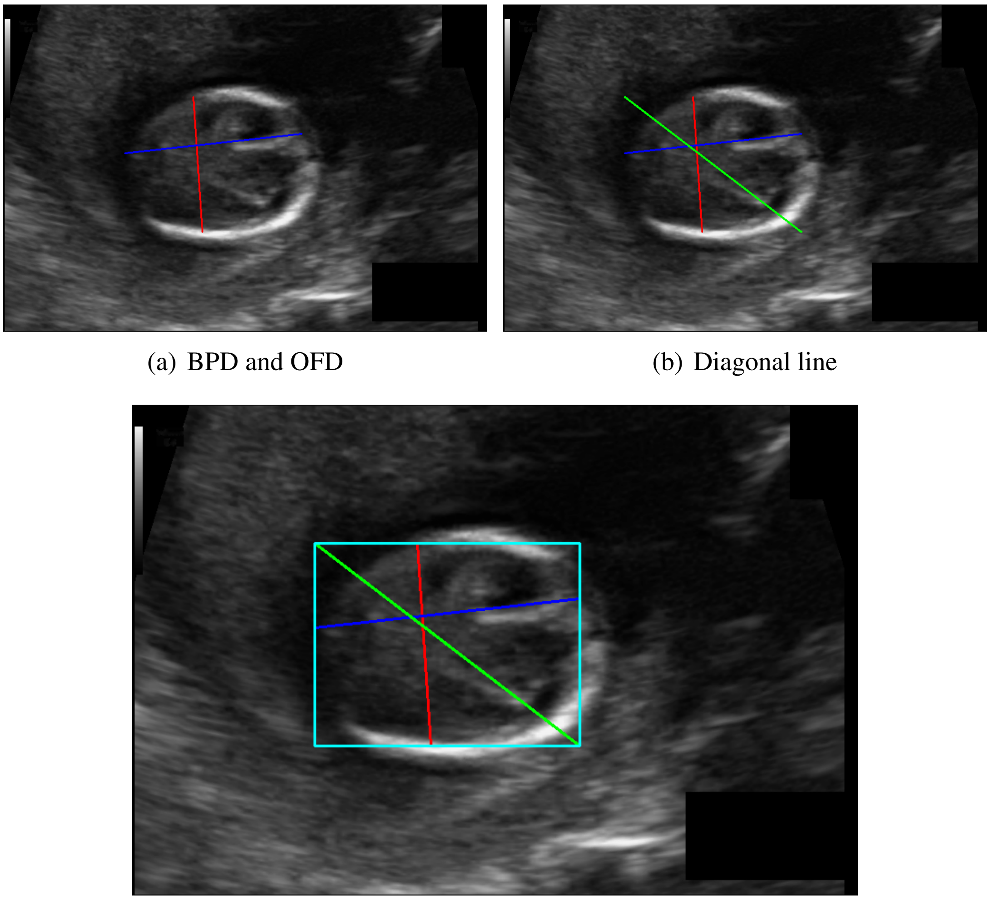
In this work, the landmark detection for biparietal diameter (BPD) and occipitofrontal (OF) points leverages the intrinsic geometry of these landmarks as radii of an ellipse. The key insight lies in recognizing that the BPD and OF can be approximated as the width and height of the ellipse, respectively. To achieve this, the proposed approach involves calculating the bounding box of the ellipse. The YOLOv5 algorithm is employed for its proficiency in object detection tasks. By considering the ellipse as a bounding box, the width and height of this bounding box correspond to the estimated BPD and OF, respectively. The process begins with the collection and annotation of a dataset comprising fetal axial images. During training, YOLOv5 learns to localize the elliptical structures associated with BPD and OF by predicting the bounding box coordinates. Post-training, the algorithm is capable of accurately localizing the landmarks in unseen images. Upon obtaining the bounding box predictions, the width and height values are extracted to yield the estimated BPD and OF. This streamlined approach not only simplifies the landmark detection process but also provides a computationally efficient solution for automated fetal biometry assessment. The experimental results demonstrate the effectiveness of the proposed methodology, showcasing the potential of YOLOv5 in accurately and efficiently detecting BPD and OF landmarks in fetal axial images.

2 Introduction

Prenatal healthcare relies heavily on accurate fetal biometry assessments to monitor the growth and development of the fetus. Among the critical biometric measurements, the biparietal diameter (BPD) and occipitofrontal (OF) distance play pivotal roles in evaluating gestational age and overall fetal health. Traditionally, these measurements are obtained through manual annotation, a time-consuming and labor-intensive process prone to inter-observer variability.

In this context, we propose an innovative approach to automate the detection of BPD and OF landmarks in fetal axial images. Recognizing the elliptical nature of these landmarks, we exploit the insight that BPD and OF can be represented as the width and height of an ellipse, respectively. The crux of our methodology lies in calculating the bounding box of this elliptical structure.

To implement this approach, we employ the YOLOv5 algorithm, a state-of-the-art object detection model known for its efficiency and accuracy. YOLOv5 is trained on a meticulously annotated dataset of fetal axial images, learning to localize the elliptical structures corresponding to BPD and OF by predicting bounding box coordinates.
Once trained, the algorithm demonstrates remarkable proficiency in accurately detecting BPD and OF landmarks in unseen images. The bounding box predictions yield immediate estimations of the width and height, providing an efficient and automated solution for fetal biometry assessment. This not only streamlines the landmark detection process but also addresses the challenges associated with manual measurements.
In this paper, we detail the methodology, training process, and evaluation results of our proposed approach. Experimental findings highlight the effectiveness of utilizing YOLOv5 for the automated detection of BPD and OF landmarks, underscoring the potential impact on prenatal diagnostics and healthcare. By integrating advanced computer vision techniques, we aim to contribute to the ongoing efforts to enhance the accuracy and efficiency of fetal biometry assessments.



(a) BPD and OFD

(b) Diagonal line

(c) Bounding box

Figure 1: Data preprocessing involves converting the provided ground truth coordinates into the YOLO format.

3 Data Preprocessing

Our dataset comprises two main files: one containing fetal axial images and the other a CSV file storing the coordinates of two straight lines, crucial for biparietal diameter (BPD) and

occipitofrontal (OF) landmark detection. To gain a comprehensive understanding of the data, we begin by plotting these straight lines onto the images, as illustrated in Figure 1a.
For the YOLOv5 model, bounding box ground truth is required. Let (x1, y1) and (x2, y2) represent the points determining the height of the bounding box, while (x3, y3) and (x4, y4) represent the points determining the width. The corners of the bounding box are defined by (x1, y3) and (x2, y4), as depicted in Figure 2b.
To adapt these coordinates into the YOLO format, we transform them into the following representation: (x-center, y-center, width, height). The resulting bounding box is visualized in Figure 1c, showcasing the YOLOv5 input format. This preprocessing step is crucial for training the model to accurately detect BPD and OF landmarks, laying the foundation for subsequent stages in our automated fetal biometry assessment.

4 Model Architecture

The proposed model architecture is based on YOLOv5, a renowned real-time object detection framework known for its efficiency and accuracy. YOLOv5 utilizes a single neural network to make predictions, making it suitable for real-time applications. To choose a YOLOv5 small architecture for faster runs and lower computational costs, you can specify one of the smaller models provided by YOLOv5. The available model architectures are typically denoted by the letters 's' (small), 'm' (medium), 'l' (large), and 'x' (extra-large). Smaller architectures have fewer parameters and are generally faster to train and run, but they may have slightly reduced accuracy compared to larger counterparts.

5 Experimental Setting

The YOLOv5 framework was downloaded from GitHub and set up on a local computer. A Python environment of version 3.9 was created, and dependencies specified in the requirements.txt file were installed. To adapt the framework for custom data, certain files were modified.

6 Hypothesis Tried

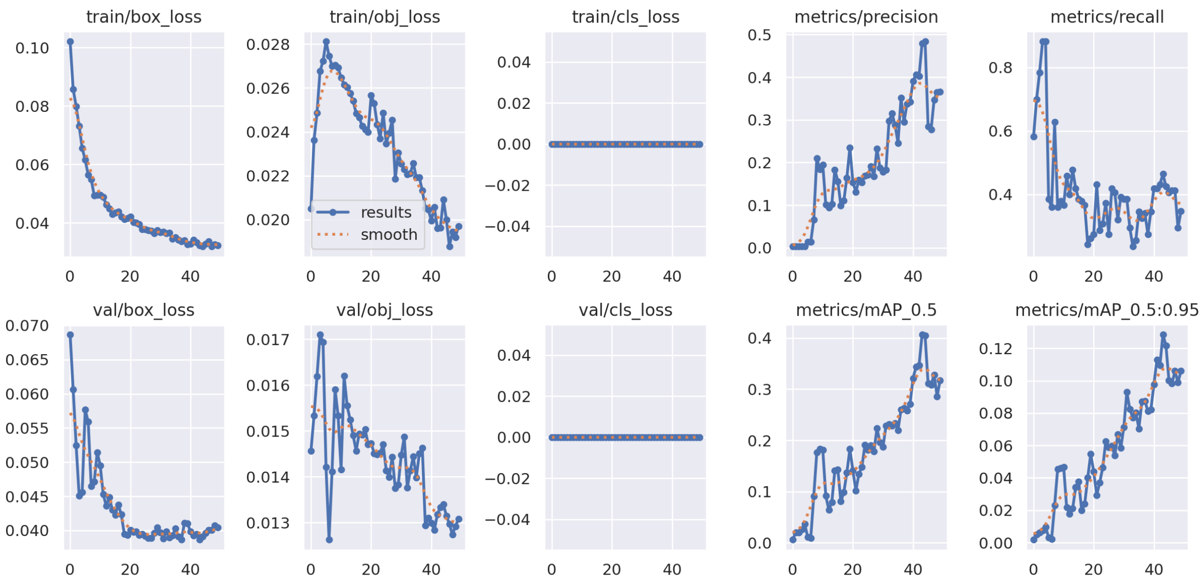
A total of 622 fetal axial images, along with their corresponding labels, were utilized in this study. To establish a robust evaluation framework, the dataset was partitioned into 452 images for training and 170 images for testing. The model training was conducted twice, with different epoch settings: firstly for 10 epochs and subsequently for 50 epochs. Hyperparameter tuning was not performed, and no alternative model architectures were explored during this phase. The evaluation of model performance is based on several key metrics, including the Loss function, Precision, Recall, and mean Average Precision (mAP). The comparison of these metrics across the two training scenarios (10 epochs and 50 epochs) provides insights into the model's learning trajectory and effectiveness in detecting biparietal diameter (BPD) and occipitofrontal (OF) landmarks in fetal axial images.
This experimental design aims to assess the impact of varying training durations on the model's performance without introducing additional complexities through hyperparameter tuning or alternative architectures. The chosen metrics offer a comprehensive evaluation, considering both the accuracy and precision of the landmark detection process.

7 Result

The model underwent training on two separate occasions, once for 10 epochs and another for 50 epochs. Various metrics were compared to evaluate the performance differences between these two experimental setups in Table 1.

Method	Architecture	Epochs	mAP	Precision	Recall	Loss
YOLOv5	YOLOv5s	10	0.123	0.19	0.37	0.02
YOLOv5	YOLOv5s	50	0.407	0.464	0.478	0.001

Table 1: **Recap of the results**. Comparing matric for 10 and 50 epochs



(a) For 50 epochs

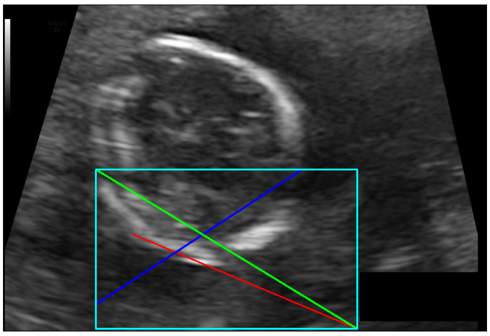
(b) For 10 epochs

Figure 2: Plot all metrics for 10 and 50 epochs

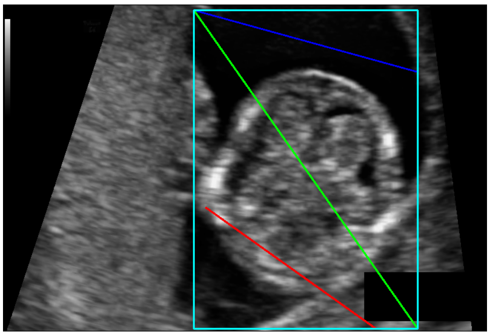
8 Key Findings

Upon analysis, it was observed that a significant portion of the images lacked correct labeling, as depicted in Figure 3a. This inconsistency in labeling may pose challenges to the accuracy of the model's predictions.

A notable limitation of the proposed approach was identified, particularly when the ellipses were placed diagonally in the images. In such cases, the algorithm encountered difficulties in accurately detecting biparietal diameter (BPD) and occipitofrontal diameter (OFD). This limitation is illustrated in Figure 3b, where the diagonal placement of ellipses resulted in reduced effectiveness of the approach.
These key findings underscore the importance of addressing labeling inconsistencies and the need for further refinement to enhance the algorithm's robustness, particularly when faced with diagonal placements of ellipses in fetal axial images.



(a) Wrong Label



(b) Diagonal Ellipse

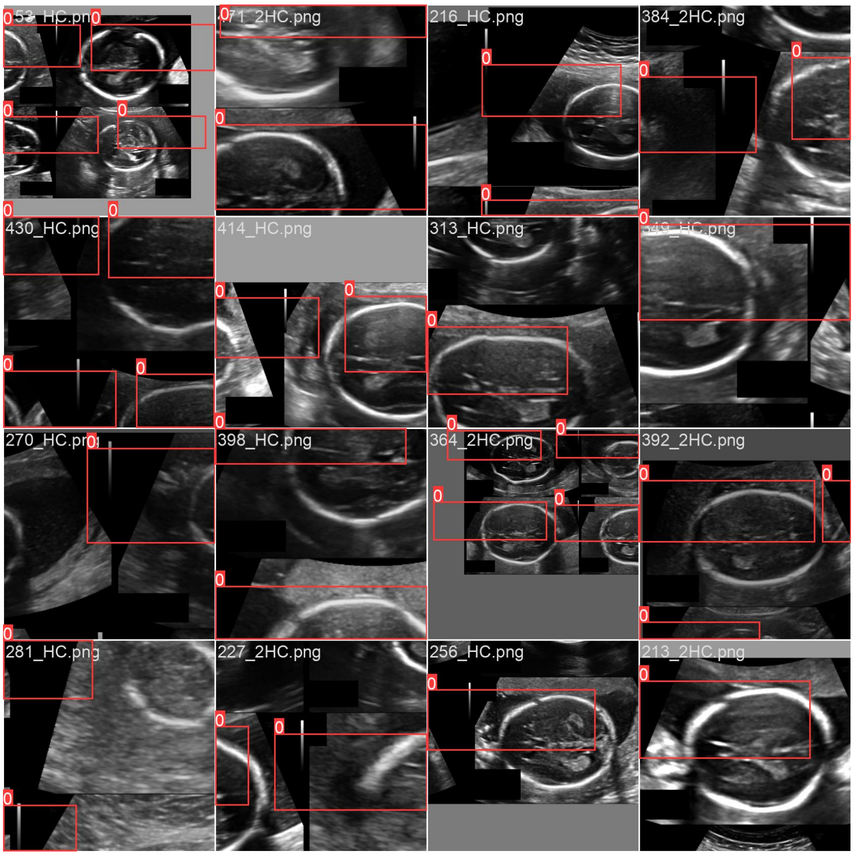
Figure 3: The first image is wrongly labeled. The second one contains the ellipse diagonally. So can't get BPD and OFD as height and width respectively

9 Future Work

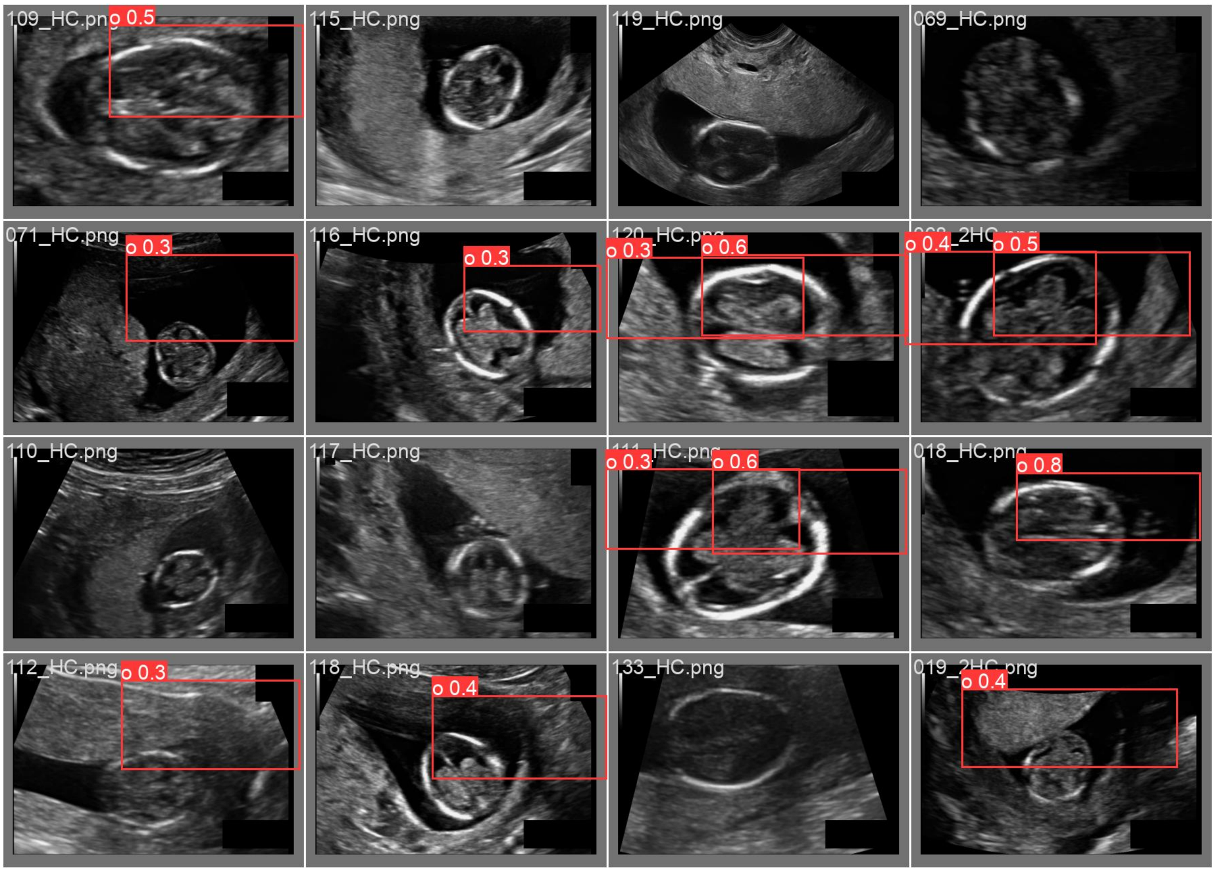
This study lays the groundwork for addressing the fetal axial image landmark detection problem. Moving forward, there is potential for improvement through hyperparameter tuning, exploring diverse model architectures beyond YOLOv5, implementing advanced data augmentation techniques, and investigating direct landmark prediction models as outlined in [1]. These avenues present opportunities to refine the current approach and enhance the accuracy and efficiency of landmark detection for biparietal diameter (BPD) and occipitofrontal diameter (OFD) in future research.

10 References

1. Christian Payer, Darko Stern, Horst Bischof, Martin Urschler. ”Regressing Heatmaps for Multiple Landmark Localization using CNNs”. Conference Paper · October 2016
2. Junfan WANG, Yi CHEN, Mingyu GAO, Zhenkang DONG. ”Improved YOLOv5 network for real-time multi-scale traffic sign detection”. 16 Dec 2021



(a) Ground truth bounding box on Images



(b) Prediction bounding box on the images

Figure 4: The bounding box of the prediction and ground truth on the images