Automated Gender Detection in an Ultrasound Image using Object Recognition

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***Abstract*— The discernment of the gender of the fetus during obstetric ultrasound has played a major in sex-selective abortions. Researchers have shown that in India, there are approximately 50,000 to 100,000 abortions per year. Though there are laws on female feticide, poor awareness and difficulty in implementing technological solutions has made it difficult to effectively dissuade such practice. In the current scenario, B-scans are displayed on monitor screens in real time, which can lead to the unnecessary display of frames that reveal the gender of the fetus. This workflow adds undue burden on the operator to take further precautions to prevent leak of the gender information. Our work not only focuses on automatically detecting ultrasound frames that contain gender but also identify the specific region of the frame that indicated the gender, so that it can be obscured during real-time display.**

Keywords—Fetal ultrasound, gender detection, Deep Learning, female feticide, Object Detection, medical imaging

I. INTRODUCTION

Medical Imaging technologies such as X-rays, Ultrasound (US), Magnetic Resonance Imaging (MRI), and Computed Tomography (CT) have revolutionized non-invasive imaging for clinical diagnostics. Among these, ultrasound is the preferred choice for obstetric scans, utilizing high-frequency acoustic waves to generate real-time images of internal structures.

The International Society of Ultrasound in Obstetrics and Gynecology (ISUOG) recommends ultrasound routines between 18 to 22 weeks of Gestational Age (GA) in pregnant women to obtain pregnancy dating, detect fetal abnormalities, and determine the gender of the baby [4]. Accurate gender identification can be achieved as early as 13 weeks of GA with a high accuracy rate of 99% to 100% [8]. The Table I shows the statistics of the accuracy of gender identification performed during different gestational ages over a wide demographic area. However, misuse of this process has led to sex-selective abortion and female infanticide in developing countries like China and India, significantly impacting global gender ratios [5][6][7]. To address this issue, India amended the Pre-conception and Pre-natal Diagnostic Techniques (PCPNDT) act in 2004 to discourage prenatal sex screening and feticide, but its enforcement faces practical challenges [3]. The need for a technological solution that combines the benefits of advanced ultrasound scanning with effective law enforcement is crucial.

Deep learning models have emerged as a promising solution due to their near-human accuracy and efficiency [1][2]. This paper explores an object detection approach to localize the gender-revealing region within ultrasound frames, allowing for better preservation of information and expanded usability for clinicians.

The subsequent sections provide a detailed methodology (Section II), present the results (Section III), discuss the implications and potential future work (Section IV), and conclusions (Section V).

TABLE I. SEX DETERMINATION ACCURACY FOR GESTATION AGES

Gestational Age	King's College Hospital Medical School [6]	Taipei City Hospital & Li Shin Hospital [7]
11 weeks	70.3%	71.9%
12 weeks	98.7%	92%
13 weeks	100%	98.3%

II. METHODOLOGY

A. Data pre-processing

Ultrasound B-scan image data were collected from GE scanner for 50 women between 12 to 20 weeks into their pregnancy using multi frequency multi focal convex probe [1]. This specific period was chosen because it aligns with the stage when the gender of the fetus becomes detectable on ultrasound images, and it also coincides with the legal limit for abortion in India, which is up until 24 weeks of pregnancy. Each patient had at least one cine-loop of images acquired, with the majority of scans capturing a top view of the fetus to ensure clear visibility of the gender area. The scans were stored in Portable Network Graphic (PNG) format and meticulously annotated and labeled by an expert sonologist, providing the size and location to mask, serving as the ground truth for subsequent analysis.

B. *Model Training and Testing*

The chosen object detection algorithm for this task was "You Only Look Once" (YOLO) [2]. As the name implies, this model provides predictions for the entire image in a single pass and utilizes Convolution Neural Networks (CNN) to generate probabilities and bounding boxes for the detected classes. For training, transfer learning was employed by utilizing weights from ImageNet pre-trained on the COCO dataset for the YOLO version 8 model, serving as a starting point for fine-tuning. Data augmentation techniques, including resizing, Gaussian noise, flipping, rotation, and scaling, were applied during training. The training process involved a dataset of 9000 images containing both complete and partial gender views, focusing on a single class, "Gender Frames," for 50 epochs. The network was optimized with a batch size of 8 and image dimensions of 640 to enhance its performance. To ensure model accuracy, the training set was split into an 80% for training and 20% for validation, respectively.

The implementation of the algorithm was done using PyTorch, and training and inference were performed on hardware equipped with an 8 GB NVIDIA GeForce RTX 3060 GPU. Following the training phase, the model underwent testing using a separate test set consisting of 500 images selected randomly. This test set contained 293 gender frames and 207 non-gender frames including brain, heart, femur, abdomen, face, spine etc. to simulate a real-time environment, with a ratio of 58.6% between the two classes [9].

III. RESULTS

TABLE II. TEST SET PERFORMANCE

Model	$AP_{0.5:0.95}$	$AP_{0.5}$	P	R	F1
YOLOv8	0.866	0.978	0.998	0.996	0.995

This section presents a detailed analysis of our model's performance on the test dataset. The hyper parameters of intersection over union (IOU) and the confidence threshold (Confthr) were set at 0.5 and 0.25, respectively. The evaluation metrics employed include the true positive rate (Recall), positive predictive rate (Precision), average precision, and F1 score (harmonic mean of precision and recall). Additionally, the average precisions for IOU > 0.5 (AP0.5) and IOU between 0.5 and 0.95 (AP [0.5:0.95]) are reported for all classes. Table II provides a comprehensive overview of the measurements obtained from the test set. Figure 1 illustrates the F1-score plotted against the confidence level, demonstrating the model's high performance with an F1 score exceeding 95%, which is comparable to the results of other studies on gender detection in ultrasound imaging [2]. Furthermore, Figure 2 showcases example images from the test set, highlighting the model's detection capabilities.

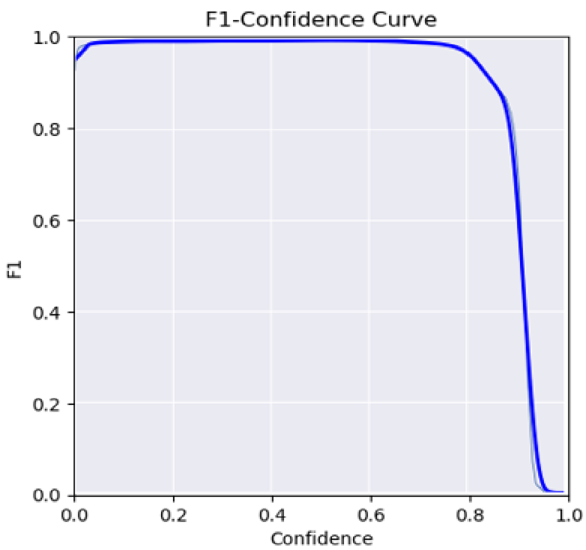


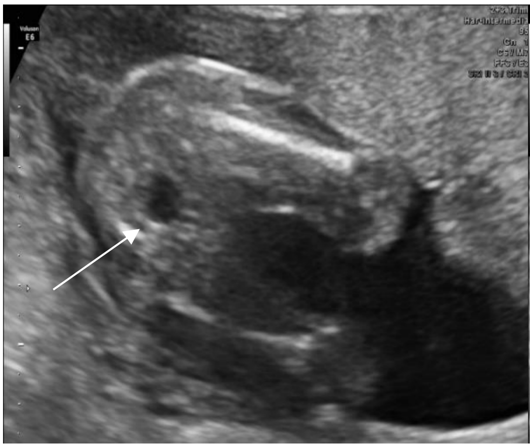
Figure 1. F1 score detection curve for YOLOv8

IV. DISCUSSION

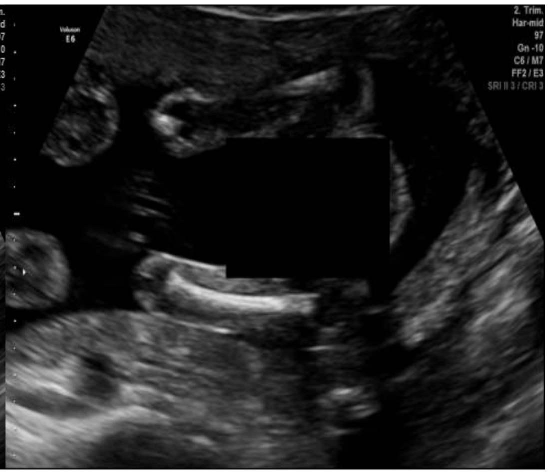
The performance metrics of our model demonstrate its effectiveness in detecting and classifying gender frames. Precision and F1 score evaluations indicate strong performance, but it is crucial to carefully analyze False Negatives (FN) and False Positives (FP) [2].

During this investigation, we achieved 100% sensitivity by fine-tuning and optimizing the model's hyper parameters by observing the test set performance, allowing it to accurately detect gender frames in both partial and ideal scenarios. This led to a high precedence of false positives but this is not an issue as the cine-loop has more non-gender frames to accommodate. Figure 2(e) displays a brain frame that was erroneously detected as a gender frame by the network. Among the 207 non-gender frames in the test set, we observed 81 false positives and zero false negatives. It should be noted that the test set includes non-gender frames as real-time data encompasses various organs and views. Nonetheless, during training, the model exclusively focused on gender frame identification, utilizing gender labels as this was the specific objective. Additionally, we optimized the size of the black box to eliminate data redundancy within each frame, further enhancing the model's performance and allowing them to be used for clinical study.

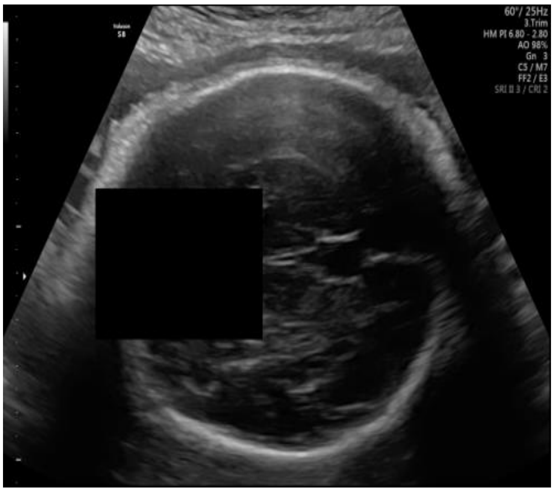
These findings highlight the potential for further refining our model and its implementation for gender detection in ultrasound imaging. Future research will concentrate on maintaining system functionality while addressing challenges associated with false positives, reproduction of the model, as well as expanding the model's applicability to real-time video analysis.

2(a) 2(b)

2(c) 2(d)



2(e)

Figure 2. Images of fetal scans where; (a), (b), (c), (d) provide the gender area that was detected and masked by the network, true positives; and (e) provides a non-gender frame that was wrongly detected by the model, a false positive.

V. CONCLUSION

This paper proposes the development of a system that uses an object detection algorithm to localize the gender area of the fetus from the ultrasound scans of the patients. This approach has the potential to not only increase the flexibility of ultrasound scanning, but also reduce the burden on the clinicians while using the technology and in effective implementation of regulatory laws.

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REFERENCES

[1] P. P. Lakra, A. Kumar, N. Mohanram, G. Krishnamurthi, and A. K. Thittai, "Deep-learning based identification of frames containing foetal gender region during early second trimester ultrasound scanning," in *2019 IEEE International Ultrasonics Symposium (IUS)*, pp. 471–474, 2019.

[2] A. Borundiya, A. Navruzyan, D. Igoschev, F. C. Oughali, H. Pasupuleti, M. Fuller, V. Kanigicherla, T. S. A. Kashyap, R. Chaurasia, and S. V. Jain, "A Deep learning Approach for Masking Fetal Gender in Ultrasound Images," in *Computer Vision and Pattern Recognition*, Sept, 2021.

[3] Population Division of Department of Economic and Social Affairs*, World Population Prospects 2019: Highlights*, ser. World Population Prospects. United Nations, 2019.

[4] L. J. Salomon, Z. Alfirevic, V. Berghella, C. Bilardo, E. Hernandez-Andrade, S. L. Johnsen, K. Kalache, K.-Y. Leung, G. Malinger, H. Munoz, F. Prefumo, A. Toi, W. Lee, and on behalf of the ISUOG Clinical Standards Committee, "Practice guidelines for performance of the routine mid-trimester fetal ultrasound scan," *Ultrasound in Obstetrics & Gynecology*, vol. 37, no. 1, pp. 116–126, 2011.

[5] E. Merz, *Ultrasound in Obstetrics and Gynecology, Volume 1 Obstetrics*. Thieme, 2011.

[6] Z. Efrat, O. O. Akinfenwa, and K. H. Nicolaides, "First-trimester determination of fetal gender by ultrasound," *Ultrasound in Obstetrics & Gynecology*, vol. 13, no. 5, pp. 305–307, 1999.

[7] C. Hsiao, H. Wang, C. Hsieh, and J. Hsu, "Fetal gender screening by ultrasound at 11 to 13+6 weeks," *Acta Obstetricia et Gynecologica Scandinavica*, vol. 87, no. 1, pp. 8–13, 2008.

[8] B. L. Whitworth, M and C. Mullan, "Ultrasound for fetal assessment in early pregnancy," *Cochrane Database of Systematic Reviews*, no.7, 2015.

[9] X. P. Burgos-Artizzu et al., "Evaluation of deep convolutional neural networks for automatic classification of common maternal fetal ultrasound planes," *Sci Rep*, vol. 10, no. 1, p. 10200, 2020.