BIDH5002 Digital Health and Data Science
Project B Capstone Project

Final Report

Exploring the Feasibility of Using Machine Learning To Improve Early Prediction of Preterm Birth

Prepared by: Vernise Ang Veng Yan / 540288036

Version: 1.0

Created on: 03/11/2024

Table of Contents

Journal Style

The journal style used for this thesis is Journal of Medical Internet Research (JMIR).

Abstract

Background: Preterm birth (PTB) remains a major global health challenge and the leading cause of neonatal morbidity and mortality. Australia's PTB rate has remained unchanged over the past decade, highlighting the importance of early detection and timely intervention. Uterocervical angle (UCA) and cervical length (CL), both measurable from routine transvaginal ultrasounds, have emerged as novel predictors of PTB risk. Traditional calculation methods are manual and time-intensive, but machine learning (ML) offers a promising solution to automate these measurements, potentially enhancing early detection. However, there remains a clear gap in research on ML applications for automating UCA and CL measurements.

Objective: This project aims to investigate the importance of predicting PTB risk and explore the feasibility of applying ML models to estimate PTB risk using UCA and CL as predictors.

Methods: CL is measured from the internal ostium (IO) to the external ostium (EO), and UCA is defined as the angle formed between the IO, inner uterine wall (IUW), and EO. To automate these measurements, an object detection model is trained to identify to identify the IO, EO, and IUW. In a retrospective study, 71 transvaginal ultrasound (TVU) images were collected from the Royal Prince Alfred Hospital (RPAH) and an open-source dataset on Mendeley Data [12]. The dataset was divided into training (70%), testing (20%), and validation (10%) sets, with TVU images annotated by drawing bounding boxes around uterocervical structures. An EfficientDet model from the Monk Object Detection library was trained on these images to evaluate the feasibility of automating anatomical landmark detection.

Results: The model stopped training at epoch 85 with a validation loss of 0.12, showing minimal progress. During testing, it was applied to detect uterocervical structures on TVU images. Out of 14 test images, only 2 had successful predictions, and across the entire dataset of 71 images, only 20 predictions were made. None of the images had complete detection of all three key structures. The model achieved a precision, recall, and F1-score of 0.45, with a mean average precision (mAP) of 0.164 and mean average recall (mAR) of 0.000719, showing difficulties in accurate detection. The average IoU of 0.142 highlighted poor alignment between predicted and ground truth boxes.

Conclusions: The EfficientDet model struggled to detect uterocervical structures, limiting its applicability for automating UCA and CL measurements. The small dataset and low image quality may have contributed to these challenges. Future work should focus on expanding the dataset and testing various object detection algorithms to improve detection accuracy. This study demonstrates the feasibility of object detection models for calculating CL and UCA. Further research is needed to refine the model to a clinical standard suitable for practical use.

Keywords: cervical length; uterocervical angle; preterm birth; object detection model; machine learning; EfficientDet

Introduction

Background

Preterm birth (PTB) is defined as the delivery of an infant before 37 weeks of gestation or 259 days from the beginning of the mothers last menstrual cycle. [1] A 10-year study by Brown stated that the North Territory has the highest rate of preterm birth within Australia. In year 2010, 10.6% of live births were preterm. In year 2020, the preterm birth percentage increased to 11.4%. This study shows that not only there was no decrease in preterm births for the past 10 years, in some regions, there was even a slight increase of the number of preterm babies. In 2020, an estimated 15 million babies were born prematurely worldwide, representing 11.1% of all live births, making PTB the primary cause of mortality among children under five globally. [2] Complications arising from PTB contribute to 35% of neonatal deaths each year and can lead to enduring health issues, including vision and hearing impairments, developmental delays, and chronic respiratory conditions. These challenges not only impact the affected children but also impose significant emotional and financial burdens on their families. [3] Thus, accurately predicting and identifying women at high risk for PTB is crucial for enabling early intervention.

UCA and CL As Novel Predictors

PTB risk has traditionally been assessed through transvaginal ultrasound (TVU), where cervical length (CL) is a widely accepted marker that can be manually measured from TVU images. [4] CL is routinely used to identify higher-risk pregnancies to allow for timely interventions. In 2016, Dziadosz discovered a positive correlation between a larger uterocervical angle (UCA) in the second trimester and the likelihood of spontaneous PTB, sparking interest in UCA as a new predictive factor. [5] Since then, several comparative studies have concluded that combining both UCA and CL enhances predictive accuracy for PTB. Numerous studies have further evaluated the effectiveness of each predictor individually and in combination, with the findings summarised in Table 1.

Study by	Predictors	P-value	Sensitivity (%)	Specificity (%)	NPV (%)
Luechathananon [6]	UCA≥110.97°	0.29	72.1	46.2	81.8
	CL<3.4 cm	0.77	65.1	43.6	77.3
	UCA≥110.97° & CL<3.4 cm	0.80	48.8	68.4	78.4
Nguyen [7]	UCA≥99°	<0.001	91	76	99
	CL≤33.8 mm	<0.001	25	66	93
	UCA≥99° & CL≤33.8 mm	<0.001	66	93	98
Dziadosz [8]	UCA>105°	<0.001	81	65	99
	CL≤25 mm	<0.001	98	29	96
	UCA>105° & CL≤25 mm	<0.001	23	98	97
Akyuni [9]	UCA>103.2°	0.219	76.9	74.19	88.46
	CL≤2.66 cm	<0.001	92.31	38.71	54.5
	UCA>103.2° & CL≤25 mm	-	90.9	78.7	96.2
Khamees [10]	UCA>105°	<0.001	86.1	60.4	92.8
	CL≤25 mm	<0.05	27.8	85.8	77.8
	UCA>105° & CL≤25 mm	<0.05	25	92.5	78.4
Movahedi [5]	UCA>106°	<0.001	46.34	85.44	92.5
	CL≤33 mm	<0.001	60.98	75.32	93.7
	UCA>106° & CL≤33 mm	0.002	56.1	86.71	93.8

Table 1. Summary of UCA and CL performance as predictors of PTB

The table above shows that combining both UCA and CL as predictors significantly enhances specificity, improving the models accuracy in identifying pregnancies likely to go full term. This improvement is further reflected in the increased Negative Predictive Value (NPV) across various studies, demonstrating a stronger capability to correctly classify term pregnancies. With both predictors, healthcare providers can better exclude low-risk cases and focus their efforts on pregnancies with a heightened risk of PTB. This proactive strategy not only ensures that high-risk pregnancies receive the necessary attention and care but also conserves hospital resources and reduces costs.

Traditional Method

In the traditional method of calculating UCA and CL, a probe is inserted along the vaginal axis until it reaches the anterior lip of the cervix at the anterior fornix. A first line is drawn from the internal ostium to the external ostium, and callipers are placed at the points where the posterior cervix walls touch the internal and external ostia along the endocervical canal to determine CL (shown as A to B in Figure 1). A second line is then drawn to mark the lower uterine segment, and the UCA is measured as the anterior angle between these two lines using a protractor (shown as the angle between lines AC and AB in Figure 1). [11] This manual measurement method is inefficient, as both the CL and UCA must be calculated manually by healthcare professionals, slowing down the risk assessment process and increasing their workload.

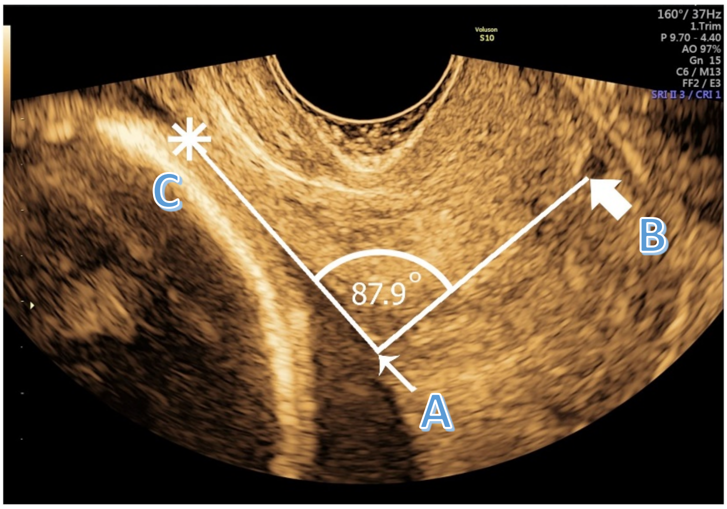


Figure 1. UCA and CL measurement from TVU

Power of Machine Learning

Machine learning (ML) has emerged as a powerful tool for pattern recognition, driving major advances in computer vision. Today, many AI applications use ML algorithms to extract insights from medical images, streamlining clinical workflows and supporting decision-making. ML can potentially be applied to automate the measurement of CL and the UCA. Since CL is already a routine measurement, only minor adjustments to the TVU probe are necessary to capture the UCA, eliminating the need for additional scans. This approach not only streamlines the assessment process but also reduces patient discomfort and optimises clinical resources.

Through a literature search, a literature gap was found in the application of ML models for automating CL and UCA measurements. To date, ML has not been used to automate these measurements. If this approach is feasible, carefully designed algorithms can be introduced as a routine calculation in clinical practice, bringing significant advancements for early PTB risk detection. The literature review also explored the validity of CL and UCA being predictors of PTB, as well as the application of machine learning models to calculate lengths and angles in the medical field. Object detection models such as You Only Look Once (YOLO), U-Net, Faster R-CNN and EfficientDet have proven to be highly effective for identifying, classifying, and measuring objects within images. These models can be applied to detect uterocervical structures (IO, EO, and IUW), which is an essential step for CL and UCA calculations. Their high accuracy and advanced feature extraction capabilities make it especially suitable for complex tasks requiring precise localisation, potentially enabling a reliable and efficient approach to automate CL and UCA measurement in clinical practice.

Study's Objective

Due to the limited application of ML in automating CL and UCA measurements, this study examines the feasibility of using ML models to automate these processes, with the goal of enhancing early PTB detection. The study also explores the importance of predicting PTB risk. Using open-source TVU images from prenatal appointments, the study focuses on identifying key uterocervical structures, including the internal ostium, external ostium, and inner uterine wall. This foundational step is crucial for future research aiming to accurately calculate CL and UCA based on these detected structures.

Methodology

Prediction Problem

The primary focus of this study is to evaluate the accuracy of a machine learning model in detecting uterocervical structures (internal ostium, external ostium, and inner uterine wall) from TVU images. This will be assessed on a per-patient basis, where each ultrasound image is analysed for the correct prediction of anatomical landmarks used to calculate CL and UCA. The study is retrospective, analysing previously collected TVU images from the RPAH and an open-source dataset. It is a prognostic study, aiming to predict preterm birth risk based on the automated measurement of UCA and CL.

Ethics Clearance and Paperwork

Ethics application was obtained. Approval was granted for an Honorary Non-Medical Appointment within the Ultrasound Department and Fetal Medicine of RPA Women and Babies located at Royal Prince Alfred Hospital (RPAH). The appointment is commencing from 01 November 2024 to 21 February 2025.

Recruitment and Data Collection

The target group for this study is women in their second trimester of pregnancy. The open-source dataset consists of samples from women between 19 and 25 weeks gestation, while samples from the Royal Prince Alfred Hospital (RPAH) are anonymous. Only singleton pregnancies were eligible for inclusion. Transvaginal ultrasound (TVU) images were manually selected using a non-probability judgment sampling method, with all identifying information removed to ensure participant anonymity. Images were included only if they offered clear visibility of the internal ostium, external ostium, and inner uterine wall. Due to the small sample size and the inclusion of only high-quality images, the study's findings cannot be generalised to the broader population. Future research should involve larger and more diverse datasets to validate and expand upon these results. This study serves as an initial foundation to create models that can be applied in larger, more comprehensive studies.

Data Preparation

A total of 71 transvaginal ultrasound (TVU) images were collected from both data sources and uploaded to the Roboflow software for annotation. Pre-processing steps, including auto-orientation and resizing to 1000x600, were applied to standardise the images. Three class labels, 'internalostium,' 'externalostium,' and 'inneruterine', were created to represent each uterocervical structure. Bounding boxes were then manually drawn around these structures, as shown in Figure 2. This process is performed under the assistance of doctors from the Royal Prince Alfred Hospital (RPAH) to ensure accurate placement. The annotated images were divided into 70% for training, 20% for testing, and 10% for validation, with the specific dataset distribution detailed in Table 2. To expand the training dataset, each training image was augmented into 3 new images using rotation (-15° to +15°) and exposure adjustments (-10% to +10%), resulting in an increase to 147 images for training. This dataset was then downloaded for use in building the object detection model.

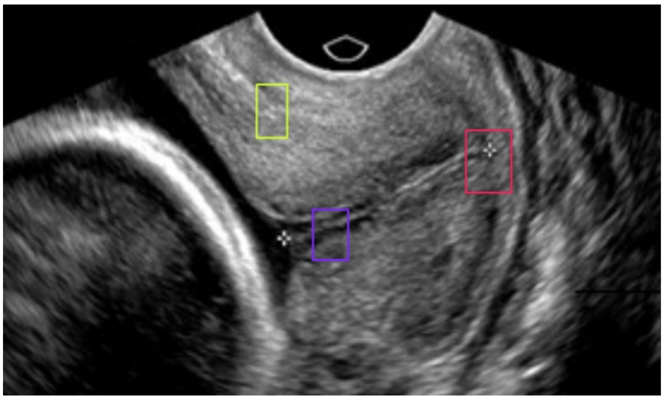


Figure 2. Bounding boxes drawn during data annotation

	Public dataset	Hospital
Training	34	15
Validation	5	3
Testing	9	5
Total	**48**	**23**

Table 2. Dataset distribution

Model Training

The Monk Object Detection Library was cloned and set up on Google Colab to facilitate model training. EfficientDet was selected as the object detection model for this project. The architecture of this model is illustrated in Figure 3. EfficentDet uses ImageNet-pretrained EfficientNet as the backbone network. A bidirectional feature pyramid network, called BiFPN, is used as the feature network. This BiFPN extracts level 3-7 features from the backbone network and repeatedly applies top-down and bottom-up bidirectional feature fusion. The network learns the importance of different input features at each scale using weighted feature fusion. EfficientDet then predicts bounding boxes and object classes using class and box prediction networks. Lastly, EfficientDet employs compound scaling to ensure that the model balances computational cost and accuracy. [13] The variant used for this project is EfficientDet-d0. This variant has similar accuracy as YOLOv3 but with 28 times fewer FLOPs. [13]

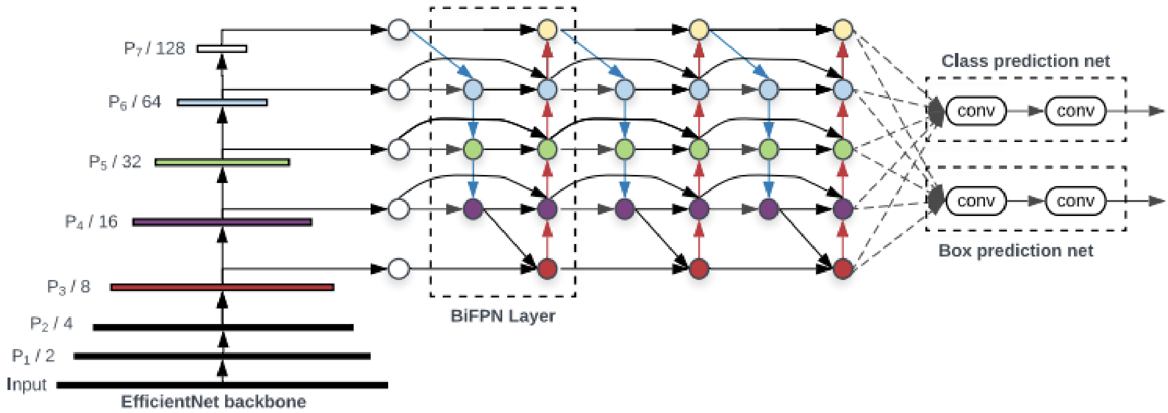


Figure 3. EfficientDet's architecture

To optimise model's performance and manage computational resources, specific hyperparameters were set. A learning rate of 0.0001 was applied to control the update step size during training. Early stopping was implemented with a minimum delta of 0.01. This prompts the model to stop training if the improvement in validation loss dropped below 0.01. An early stopping patience of 3 epochs was set, stopping training if no progress in validation loss was observed over 3 consecutive epochs. As a result, the EfficientDet-d0 object detection model training concluded at epoch 85, where validation loss maintained around 0.12, showing minimal improvement. This stopping point was also influenced by the limited GPU resources provided by Google Colab. The total validation loss was visualised in a graph, as shown in Figure 4.

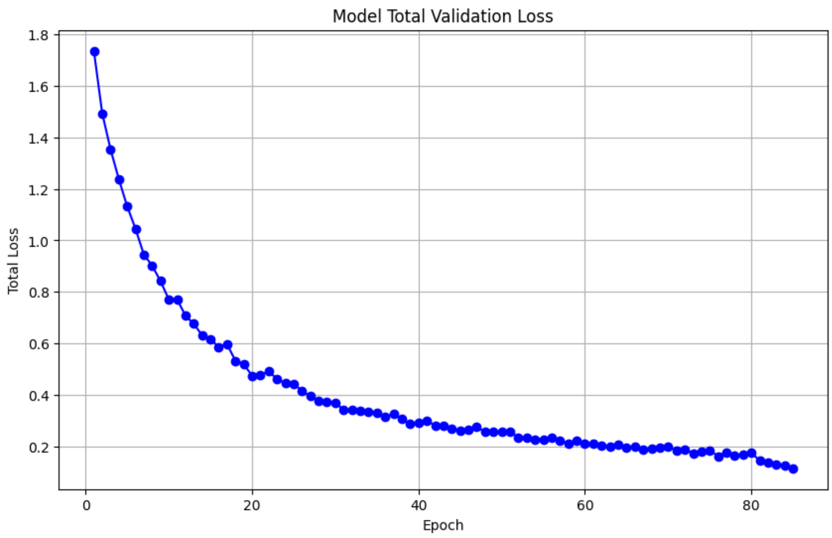


Figure 4. Graph of model training's total validation loss over 85 epochs

Model Testing

The trained object detection model was inferenced and used to perform predictions on TVU images. Among the 14 testing images, the model successfully made predictions on only 2 images, resulting in a total of 3 detected structures, as presented in Table 3. Neither of the images had predictions for all 3 uterocervical structures. Figure 5 visualises the models predictions for one of these images (14.jpg). To further explore the model's predictive power, the full dataset of 71 collected images was used for additional testing. Despite the expanded dataset, the model produced only 20 predictions, displayed in Table 4. Figure 6 visualises predictions for one of these images (4.jpg).

Image	Class	Class ID	Score	Box_xmin	Box_ymin	Box_xmax	Box_ymax
/content/gdrive/MyDrive/capstone/testing/14.jpg	externalostium	1	0.06322910637	301.8475342	208.828598	330.5056152	235.3984833
/content/gdrive/MyDrive/capstone/testing/14.jpg	internalostium	3	0.05279128253	266.1501465	208.7951355	300.2662354	230.4420166
/content/gdrive/MyDrive/capstone/testing/17a.jpg	internalostium	3	0.09227421135	252.4478302	216.0541077	281.078125	240.8085327

Table 3. Predictions for 14 testing images

Figure 5. Sample visualisation of prediction from testing set

Image	Class	Class ID	Score	Box_xmin	Box_ymin	Box_xmax	Box_ymax
/content/gdrive/MyDrive/capstone/extratesting/17b.jpg	internalostium	3	0.05260665342	250.3659973	201.5093384	284.8244324	223.4131775
/content/gdrive/MyDrive/capstone/extratesting/hospital5.jpg	externalostium	1	0.06311426312	302.0341187	135.0770416	330.3565063	160.0116425
/content/gdrive/MyDrive/capstone/extratesting/hospital5.jpg	internalostium	3	0.06044669822	200.9824524	240.6730194	234.5954895	262.9522705
/content/gdrive/MyDrive/capstone/extratesting/30a.jpg	internalostium	3	0.05117415637	242.405899	256.9876404	278.0091248	278.8379211
/content/gdrive/MyDrive/capstone/extratesting/22.jpg	externalostium	1	0.05822777376	333.5984802	157.3421783	362.8802185	183.7632904
/content/gdrive/MyDrive/capstone/extratesting/18.jpg	inneruterine	2	0.06004589051	340.4762878	151.3128967	369.4338684	177.2078247
/content/gdrive/MyDrive/capstone/extratesting/21.jpg	internalostium	3	0.09155296534	243.1797485	200.245697	278.8222046	221.9571533
/content/gdrive/MyDrive/capstone/extratesting/17.jpg	internalostium	3	0.1529365927	251.0529175	231.6389313	283.1838379	254.0641937
/content/gdrive/MyDrive/capstone/extratesting/17c.jpg	internalostium	3	0.07974974066	226.0840759	233.2103729	256.5520935	254.3927765
/content/gdrive/MyDrive/capstone/extratesting/3a.jpg	internalostium	3	0.05326687917	250.6144867	224.4873962	284.8774719	245.8145142
/content/gdrive/MyDrive/capstone/extratesting/4.jpg	internalostium	3	0.1134599894	258.1075745	192.8812866	291.7512512	213.6585083
/content/gdrive/MyDrive/capstone/extratesting/4.jpg	inneruterine	2	0.05970045924	175.2877502	112.2649002	206.8108826	134.3642426
/content/gdrive/MyDrive/capstone/extratesting/4a.jpg	internalostium	3	0.1125617027	247.4175873	201.5962067	281.4910278	222.2846527
/content/gdrive/MyDrive/capstone/extratesting/9a.jpg	internalostium	3	0.08709896356	236.3522949	239.8457184	270.4935303	262.0722656
/content/gdrive/MyDrive/capstone/extratesting/8a.jpg	internalostium	3	0.07137531787	249.9299927	184.3115692	285.0322266	206.7969208
/content/gdrive/MyDrive/capstone/extratesting/17a.jpg	internalostium	3	0.1013776958	247.7703247	216.9555969	281.7990112	238.6087036
/content/gdrive/MyDrive/capstone/extratesting/14.jpg	externalostium	1	0.07247783989	301.9196472	208.8541412	330.5729065	235.3575897
/content/gdrive/MyDrive/capstone/extratesting/14.jpg	internalostium	3	0.05529284105	266.3323975	208.7872772	300.432312	230.3773041
/content/gdrive/MyDrive/capstone/extratesting/hospital10.jpg	internalostium	3	0.06852385402	211.9135742	289.238739	244.4634399	311.0488586
/content/gdrive/MyDrive/capstone/extratesting/hospital6.jpg	inneruterine	2	0.05372326076	293.9577637	104.2555237	326.8115845	125.9825745

Table 4. Predictions for full dataset (71 images)

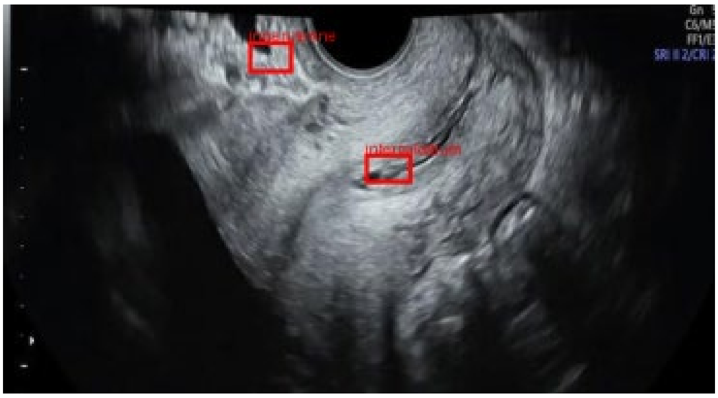


Figure 6. Sample visualisation of prediction from full dataset

Results

The evaluation metrics used to evaluate the trained EfficientDet model are precision, recall and F1-score, intersection over union (IoU), mean average precision (mAP) and mean average recall (mAR). Precision assesses the model's accuracy in predicting relevant objects, while recall measures its ability to find all relevant objects among ground truths. The F1-score balances precision and recall. IoU calculates the overlap between predicted and ground truth bounding boxes, as shown in Figure 7. Average precision (AP) represents the area under the precision-recall curve for each class, while mAP averages AP across all classes, evaluating the model's accuracy in detection and localisation. mAR averages the maximum recall values achieved at each IoU threshold, measuring the models ability to detect objects across different levels of localisation precision. [14] The IoU threshold is set to 0.01 to allow flexibility in exploring the model's detection performance across various overlap levels. For future improvements, this threshold should ultimately be increased to enhance localisation accuracy.

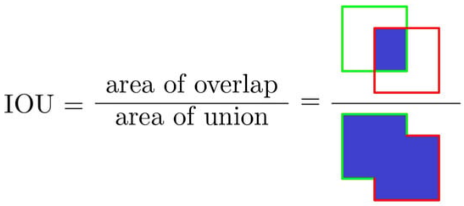


Figure 7. Intersection over union (IoU) [14]

Evaluation results are shown in Table 5. The EfficientDet model achieved precision, recall, and F1 scores of 0.45, indicating moderate performance. However, the low mAP of 0.164 suggests that, on average, the model has limited accuracy in closely aligning its predicted bounding boxes with the ground truth across all classes. The extremely low mAR of 0.000719 indicates difficulty in detecting a large portion of relevant objects, often resulting in missed true positives. This is further reflected in the low average IoU of 0.142, revealing poor alignment between the predicted boxes and ground truth annotations.

Evaluation metrics	**Value**
Precision	0.45
Recall	0.45
F1-Score	0.45
Average IoU	0.1422958311025959
mAP	0.16368102796674225
mAR	0.0007187917902203531

Table 5. Evaluation metrics of EfficientDet Model

Discussion

The evaluation results indicate that the EfficientDet model performs poorly in both detection rates and localisation accuracy. This outcome can be attributed to 2 primary reasons.

Firstly, the small dataset size and diversity is a significant limitation. Deep learning models, especially models with complex architectures like EfficientDet, rely on large, diverse datasets to effectively learn and generalise to unseen data. In this project, a relatively small dataset of only 71 TVU images was used to train the model. This limited number of samples restricts the model to capture the full variability of the uterocervical structures that it might encounter in real-world clinical settings, affecting the model's ability to generalise and detect key structures accurately in previously unseen TVU images.

Furthermore, the quality of the images also has an influence on the model's performance. According to clinicians at RPAH, CL measurement via TVU is a routine prenatal care for monitoring pregnant women, whereas UCA measurements are less common and only performed when there are indications of potential PTB. This difference in focus means that sonographers typically concentrate on the endocervical canal during CL assessments, often resulting in the lower uterine segment excluded from their imaging. This issue introduces a challenge during data annotation, as it becomes more difficult to precisely label the inner uterine wall. As a result, the dataset used in this study may not adequately capture the inner uterine wall structure necessary for accurate UCA detection and prediction, ultimately affecting the model's localisation accuracy and ability to reliably detect key structures.

To address these limitations, future research should prioritise expanding the dataset by including more TVU images from other hospitals and medical facilities. This approach would expand and diversify the dataset, reducing institutional biases and improving the models generalisability to different clinical and imaging variations in TVU scans. Future studies could also focus on collecting TVU images specifically for UCA imaging ensuring that both the endocervical canal and lower uterine segment are consistently included in each scan. This would provide a clear view of the inner uterine wall in all images, which is essential for the model to accurately detect key uterocervical structures. Additionally, future research could explore alternative object detection models,such as YOLO or Faster R-CNN, and compare their performance across key metrics. This would help identify the most suitable architecture for accurately detecting uterocervical structures in TVU images. Comparative analysis may also reveal strengths or weaknesses in each model, potentially leading to further optimisations or model adaptations tailored to the specific challenges of UCA and CL detection.

Conclusion

While this research demonstrates the feasibility of using the EfficientDet model to detect UCA and CL structures in TVU images, several challenges currently limit the model's performance and effectiveness. This study highlights both the potential of object detection models for automating the early prediction of PTB and its limitations. Despite these challenges, the findings provide a solid foundation for further research in this area. By addressing these limitations and refining existing approaches, this methodology has the potential to significantly enhance the automation of PTB risk detection. Automating the measurement of UCA and CL could reduce clinician workload, improve diagnostic accuracy, and enable more timely interventions to prevent PTBs. Future advancements in this field could play a crucial role in early detection and intervention strategies, ultimately benefiting both maternal and fetal health.

References

1. Lumley J. Defining the problem: the epidemiology of preterm birth. *BJOG: An International Journal of Obstetrics & Gynaecology*. 2003;110(s20):3-7. doi:https://doi.org/10.1046/j.1471-0528.2003.00011.x

2. Althabe F, Howson CP, Kinney M, Lawn J. *Born Too Soon : The Global Action Report on Preterm Birth*. World Health Organization; 2012.

3. Howson CP, Kinney MV, McDougall L, Lawn JE. Born Too Soon: Preterm birth matters. *Reproductive Health*. 2013;10(S1). doi:https://doi.org/10.1186/1742-4755-10-s1-s1

4. Korkmaz N, Huseyin Kiyak, Gokhan Bolluk, Olgu Bafali, Ince O, Gedikbasi A. Assessment of utero-cervical angle and cervical length as predictors for threatened preterm delivery in singleton pregnancies. *Journal of Obstetrics and Gynaecology Research*. 2023;50(1):65-74. doi:https://doi.org/10.1111/jog.15823

5. Minoo Movahedi, Goharian M, Rasti S, Elaheh Zarean, Mohammad Javad Tarrahi, Zahra Shahshahan. The uterocervical angle-cervical length ratio: A promising predictor of preterm birth? *International Journal of Gynecology & Obstetrics*. 2024;165(3):1122-1129. doi:https://doi.org/10.1002/ijgo.15361

6. Luechathananon S, Songthamwat M, Chaiyarach S. Uterocervical Angle and Cervical Length as a Tool to Predict Preterm Birth in Threatened Preterm Labor. *International Journal of Women's Health*. 2021;Volume 13:153-159. doi:https://doi.org/10.2147/ijwh.s283132

7. Nguyen TTH, Vu TV, Nguyen HVQ. Uterocervical angle and cervical length measurements for spontaneous preterm birth prediction in low-risk singleton pregnant women: a prospective cohort study. *Archives of Gynecology and Obstetrics*. 2024;310(3):1611-1619. doi:https://doi.org/10.1007/s00404-024-07646-4

8. Dziadosz M, Bennett TA, Dolin C, et al. Uterocervical angle: a novel ultrasound screening tool to predict spontaneous preterm birth. *American Journal of Obstetrics and Gynecology*. 2016;215(3):376.e1-376.e7. doi:https://doi.org/10.1016/j.ajog.2016.03.033

9. Qurrata Akyuni, Agus Sulistiyono, Hermanto Tri Joewono, Lilik Djuari. Uterocervical Angle Anterior, Posterior, and Cervical Length Ultrasound as a Predictors for Successful Delay in Labor of Pregnant Women with Threatened Preterm Birth (PTB). *Pharmacognosy Journal*. 2023;15(1):52-56. doi:https://doi.org/10.5530/pj.2023.15.8

10. Khamees RE, Khattab BM, Elshahat AM, Taha OT, Aboelroose AA. Uterocervical angle versus cervical length in the prediction of spontaneous preterm birth in singleton pregnancy. *International Journal of Gynecology & Obstetrics*. 2021;156(2). doi:https://doi.org/10.1002/ijgo.13629

11. Elmaraghy AM, Shaaban SMA, Elsokkary MS, Elshazly ISMA. Uterocervical angle versus cervical length in the prediction of spontaneous preterm birth in women with history of spontaneous preterm birth: a prospective observational study. *BMC Pregnancy and Childbirth*. 2023;23(1). doi:https://doi.org/10.1186/s12884-023-05977-9

12. Farràs A. Study dataset: Real-time ultrasound demonstration of uterine isthmus contractions during pregnancy. *Mendeley Data*. 2023;1. doi:https://doi.org/10.17632/s27zfxgbpj.1

13. Tan M, Pang R, Le QV. EfficientDet: Scalable and Efficient Object Detection. *2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*. Published online June 2020:10778-10787. doi:https://doi.org/10.1109/cvpr42600.2020.01079

14. Padilla R, Passos WL, Dias TLB, Netto SL, da Silva EAB. A Comparative Analysis of Object Detection Metrics with a Companion Open-Source Toolkit. *Electronics*. 2021;10(3):279. doi:https://doi.org/10.3390/electronics10030279

Supplementary Materials

Logbook

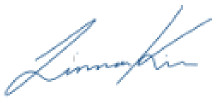
Logbook for BIDH5001 and BIDH5002: Capstone Project

Tasks	Hours spent
Set up future schedules	5
Create Gantt Chart	3
Initial research	10
Collect small dataset	10
Learning contract	2
Complete literature review OLE	3
Project proposal	10
Complete ethics application and paperwork	30
Conduct research for literature review	10
Collect full dataset	20
Image pre-processing	2
Build image detection model	40
Progress report 1	5
Build angle and length calculation algorithm	5
Build predictive machine learning model	5
Progress report 2	5
Model evaluation	10
Literature review	30
Prepare for major presentation	40
Major presentation	8
Model fine-tuning and evaluation	20
Final report	45
Total hours:	318

Verified by:

Jinman Kim

12/11/24



Learning contract

Learning Contract

Project Title: A Machine Learning Image Analysis Approach to Improve Early Prediction of Preterm Birth

Project background

Preterm birth remains a significant challenge in fetal medicine healthcare. This project aims to improve the prediction of preterm birth risk by applying machine learning techniques. Research has established the uterocervical angle (UCA) and cervical length as important predictors of preterm birth. By focusing on the UCA and cervical length, this project seeks to improve the performance of risk prediction models for preterm birth.

Purpose of project

The objective of this project is to:

- Create an object detection model to detect and calculate the uterocervical angle (UCA) and cervical length
- Build a machine learning predictive model to predict the risk of preterm birth

Project period

29 Jul 2024 to 24 Nov 2024

Project client

Fetal Medicine Unit of Royal Prince Alfred Hospital

Project supervisor

Dr. Ritu Mogra – Head of department
Professor Jinman Kim
Saleem Ahmed Khan
Karina Ray

Project outline

Deliverables:

- Project proposal (week 4)
- Progress report 1 (week 6)
- Progress report 2 (week 8)
- Major presentation (week 10/11)
- Literature review (week 12)
- Final report (exam week)

Meeting schedule:

- Weekly online meetings with Karina
- Weekly in-person meetings with Ritu
- Recurrent meetings with Professor Jinman

Objectives of learning to develop and where student is placed as part of the team

- Strengthen knowledge and application of machine learning and computer vision skills
- Obtain knowledge of preterm birth, uterocervical angle, cervical length and fetal medicine
- Collaborate with stakeholders including professors, supervisors and RPA's Fetal Medicine Unit to build a feasible solution to improve prediction of preterm birth risk

Workplace permission
Paperwork for an Honorary Non-medical Appointment has been submitted.

Health check clearances
Paperwork within the Honorary Non-medical Appointment submission include health check clearances (ex: vaccinations).

Ethics clearances
Ethics clearance has been obtained.

Project timeline:

Tasks	Weeks	Number of weeks
Set up meeting schedules	1	1
Create Gantt Chart	1	1
Initial research	1	1
Learning contract	1-2	2
Complete literature review OLE	1-3	3
Collect small dataset	2	1
Complete project proposal	2-4	3
Complete paperwork for hospital	2-4	3
Conduct research for literature review	2-5	4
Collect full dataset	4	1
Complete image pre-processing	4-5	2
Build image detection model	5-6	2
Complete progress report 1	6	1
Build angle and length calculation algorithm	6-7	2
Build predictive machine learning model	7-8	2
Complete progress report 2	8	1
Model evaluation	9-10	2
Literature review	6-12	7
Prepare for major presentation	9	1
Major presentation	10	1
Model fine-tuning and evaluation	11-13	3
Final report	12-15	4

Risk and mitigation strategies
The ultrasound data used in this project are exclusively collected from patients at the Royal Prince Alfred Hospital (RPA). This limited geographic and demographic data source can introduce bias into the final model, potentially affecting its generalisability.

To address bias and improve generalisation, future plans should include collecting ultrasound data from a diverse set of hospitals and patient groups. Data augmentation and cross-validation should be performed to detect and reduce potential biases.

Signatures from supervisors:

Ritu Mogra

Dr Ritu Mogra
Date 09/08/2024

Honorary Non-Medical Appointment Approval Letter

Health
Sydney
Local Health District

Ms Vernise Veng Yan Ang
Ultrasound Department and Fetal Medicine
RPA Women and Babies
Royal Prince Alfred Hospital

Re: Honorary Non-Medical Appointment

Dear Vernise,

I am pleased to advise that approval has been granted for an Honorary Non-Medical Appointment within the Ultrasound Department and Fetal Medicine of RPA Women and Babies located at Royal Prince Alfred Hospital (RPAH).

The appointment is commencing from 01 November 2024 to 21 February 2025.

The nature of the honorary appointment is that you are not a staff member employed by the hospital, and you will not receive any wages or salary in relation to the appointment.

I do advise that you are still expected to comply with NSW Health, Sydney Local Health District and RPAH policies and procedures including the NSW Health Code of Conduct. I have attached a copy for your information and reference. Please sign and return this to Marcus Wong, Workforce Officer.

Should you have any questions in relation to this please contact the Workforce Services Department on 9515 9888 or 9515 9524.

I welcome your contribution to Sydney Local Health District.

Yours sincerely

Marcus Wong

Marcus Wong
Workforce Officer, Royal Prince Alfred Hospital
Date: 23 October 2024.

Cc: Dr Ritu Mogra, Head of Department, Ultrasound Department and Fetal Medicine
RPA Women and Babies
Attachment: NSW Health Code of Conduct

Codebase

The codebase is uploaded to GitHub, which is accessible from the following link:

https://github.sydney.edu.au/vang0577/capstone

Alternatively, the codebase and files created are uploaded to Google Drive. The Google Colab notebook codebase is directly integrated with this Drive and can be directly run here. The Google Drive can be accessed with this link:

https://drive.google.com/drive/folders/1DSQGbOY3uV3PFgTfPNsNZD5VTkFM2bfu?usp=sharing