BIDH5002: Literature Review

A Machine Learning Image Analysis Approach To Improve Early Prediction of Preterm Birth

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Abstract

Preterm birth (PTB) remains a significant global health challenge to this day, being the main cause for neonatal morbidity and mortality. Preterm babies face serious health risk which could impact their whole life, including visual and hearing impairments, developmental delays, and chronic lung disease. Therefore, early prediction is crucial for timely intervention and improving health outcomes for both mothers and babies. There are two novel predictors of PTB — uterocervical angle (UCA) and cervical length (CL). These predictors can be easily calculated from a routine transvaginal ultrasound scan and have shown to have high relevance with PTB. Many research was conducted on the prediction of PTB using UCA, CL or both of the predictors. In recent years, machine learning has shown great contribution to the medical field. Many object detection models were used in medical imaging to streamline the diagnosis process and reducing the workload for health professionals. However, there is a clear gap in literature for the application of machine learning on the calculation of UCA and CL, following with the prediction of PTB with these measurements. This literature review aims to address this literature gap and improve the automation of PTB prediction.

Introduction

Machine learning (ML) is a rapidly advancing branch of computational algorithms that aim to replicate human intellect through data-driven learning. [1] ML algorithms teach computers to perform activities with predetermined goals without explicitly programming the rules necessary to accomplish such tasks. [2] These algorithms undergo a training process where they automatically adjust their architecture through repeated exposure to data, enabling them to progressively improve their performance on specific tasks. ML techniques are applied across various domains, including spacecraft engineering, finance, entertainment, computational biology, and medical applications. There are three main types of ML: supervised learning, unsupervised learning, and semi-supervised learning. In supervised learning, the algorithm is trained with input data paired with known classification labels. In contrast, unsupervised learning allows the algorithm to discover patterns in the input data without pre-labelled outcomes, gradually refining its internal parameters to approach the desired results. Semi-supervised learning combines both approaches, using a mix of labelled and unlabelled data, with the labelled data guiding the learning process for the unlabelled portion. [1] The performance of machine learning (ML) models on unseen data, called generalisability, is crucial for clinical applications. Balancing training and testing performance is key, especially in handling rare occurrences that may be underrepresented in the training data. For clinical decision-making, unsupervised approaches may be more effective in identifying rare instances compared to supervised methods, which focus on patterns learned during training. [2]

ML has become a powerful tool for pattern recognition, leading to significant breakthroughs in computer vision over the last decade. Many artificial intelligence (AI) applications now use ML algorithms to extract valuable insights from medical images, streamlining clinical workflows and assisting in decision-making processes. Recently, ML tools have matured to meet clinical standards, encouraging collaboration between clinical teams and companies to develop AI-driven solutions for healthcare. [3] Successful attempts to use transvaginal (TVS) ultrasound imaging data have emerged in the past few years. Several studies have employed deep learning methods to predict preterm birth (PTB) using ultrasound, MRI images, and high-dimensional HER data. [4]

Preterm birth (PTB) is defined as the delivery of a baby before 37 completed weeks of gestation or 259 days from the first day of the mothers last menstrual period. [5] This issue remains as a major global health concern. In Australia, the Northern Territory reported the countrys highest PTB rate, reaching 10.6% in 2010. By 2024, this rate had risen to 11.4%. A 10-year study indicates that not only has there been no reduction in PTB rates, but there has also been a slight rise in certain regions. [6] Globally, approximately 15 million babies were born preterm in 2020, accounting for 11.1% of live births, making PTB the leading cause of death among children under five years old worldwide. [7]

Complications from PTB account for 35% of annual neonatal deaths and can result in long-term health challenges, such as visual and hearing impairments, developmental delays, and chronic lung disease. These issues not only affect the infants but also place a considerable emotional and financial strain on their families. [8] Accurate prediction and early identification of women at high risk for PTB are essential, as they enable timely intervention.

The growing power of ML techniques offers great potential in predicting PTB by processing and analysing large, complex datasets such as medical images, genetic information, and patient health records. In particular, deep learning has contributed greatly to medical image analysis. Convolutional neural networks (CNNs) have become a widely used tool in developing high-performance models, particularly for object detection tasks. For example, one study successfully developed an object detection model to segment the cervix from transvaginal ultrasound images, paving the way for further applications like calculating cervical length, which is a key predictor of PTB risk. [9]

Object detection algorithms are commonly used in the medical image analysis domain in order to detect the initial abnormality symptoms of patients. A CNN based object detection model accepts input and runs it through convolutional layers containing filters to detect edges and boundaries with other features to detect objects in images. Object detection techniques aim to localize and classify objects in each image that run through the CNN. [10] To build a custom object detection model, an image dataset should be collected and annotated. The images and annotation labels are then used for training a CNN algorithm. Finally, the trained model should be tested with a testing image dataset to check if the model is doing its job right.

Object detection algorithms are widely applied in medical image analysis to identify early signs of abnormalities in patients. A CNN-based object detection model processes input images through multiple convolutional layers equipped with filters that detect edges, boundaries, and other features crucial for identifying objects. The primary goal of object detection techniques is to both localise and classify objects within each image processed by the CNN. [10] To develop a custom object detection model, an image dataset must be collected and annotated. These images and their corresponding labels are then used to train the CNN. Finally, the trained model is tested on a separate dataset to evaluate its accuracy and performance. [11]

A literature search revealed no existing studies that uses machine learning to automate the calculation of the uterocervical angle (UCA) and cervical length (CL), which are important predictors for assessing the risk of PTB. Despite the growing use of machine learning techniques in medical image analysis, there is a clear gap in applying these methods to automate these two measurements. This literature review seeks to address this gap by exploring the potential of machine learning models for automating UCA and CL calculations, assessing relevant studies in adjacent fields, and proposing directions for future research. Current manual methods for measuring UCA and CL are time-consuming, subject to human error, and require specialised expertise. Introducing automated approaches can streamline the process, reduce variability in measurements, and make these important predictors more accessible. This could also enable clinicians to analyse large volumes of patient data with higher precision, thereby reducing healthcare costs and improve patients' health outcomes. By filling this gap, the review aims to contribute to advancing prenatal care through the development of more efficient and accurate diagnostic tools.

Objectives

The primary objectives of this literature review are to validate the uterocervical angle (UCA) and cervical length (CL) as reliable predictors of preterm birth (PTB), examine the potential for combining these predictors, and compare their effectiveness with existing methods. Additionally, this review aims to explore current applications of machine learning techniques for object detection and

PTB risk prediction. By evaluating relevant research, the review will guide the development of a machine learning model to automate UCA and CL calculations for predicting PTB risk. The review will begin by examining studies that identify UCA and CL as PTB predictors, followed by a discussion of existing object detection models. Finally, it will address potential applications of these models for automating UCA and CL measurements.

Search Strategy Methodology

Two literature searches were performed. The first search was to learn the reliability of UCA and CL as predictors of PTB risk. The second search was to explore the applications of machine learning model in detecting uterocervical angle and/or cervical length. This review is performed on Medline via Ovid, Scopus and PubMed.

Uterocervical angle and cervical length as predictor for preterm birth

The keywords for this search are 'uterocervical angle', 'cervical length', and 'preterm', with the Boolean operator 'AND' used to ensure all results include both UCA and CL in predicting PTB. Synonyms of these keywords are also included.

Scopus

In Scopus, the field code 'TITLE-ABS-KEY' was applied to retrieve papers where keywords appear in the title, abstract, or keywords. The full search term used was TITLE-ABS-KEY ("uterocervical angle") AND TITLE-ABS-KEY ("cervical length") AND TITLE-ABS-KEY ("preterm"), resulting in 53 papers.

Medline via Ovid

The exact term 'uterocervical' returned 168 papers, while 'cervical length' OR an exploding search on 'Cervical Length Measurement' returned 2,529 papers. To focus on PTB, three additional sub-searches were conducted: the first used 'preterm' OR exploding on 'Infant, Premature,' yielding 68070 papers; the second used 'early delivery' OR exploding on 'Delivery, Obstetric' and 'Premature Birth,' returning 116494 papers; and the third used 'early labour,' returning 258 papers. These three sub-searches were combined with the Boolean OR, producing 179592 papers. Finally, combining all three main searches with 'AND' reduced the results to 36 papers.

# ▲	Searches	Results	Type
1	uterocervical.mp.	168	Advanced
2	cervical length.mp. or exp Cervical Length Measurement/	2529	Advanced
3	exp Infant, Premature/ or exp Premature Birth/ or preterm.mp.	137070	Advanced
4	early delivery.mp.	738	Advanced
5	early labour.mp. or exp Delivery, Obstetric/	94942	Advanced
6	3 or 4 or 5	225334	Advanced
7	1 and 2 and 6	48	Advanced

Figure 1: Search strategy for Medline via Ovid database

PubMed

The search term used is uterocervical AND cervical length AND (preterm OR premature OR early delivery OR early labour). 49 documents were returned.

138 records were identified in Scopus, Medline, and PubMed and duplicated records were removed. After title and abstract screening, record with duplicated authors, not focused on PTB or unrelated to the project were excluded. Records were then checked for eligibility, resulting in 14 studies included in the analysis. A summary of the literature search process is shown in the figure below:

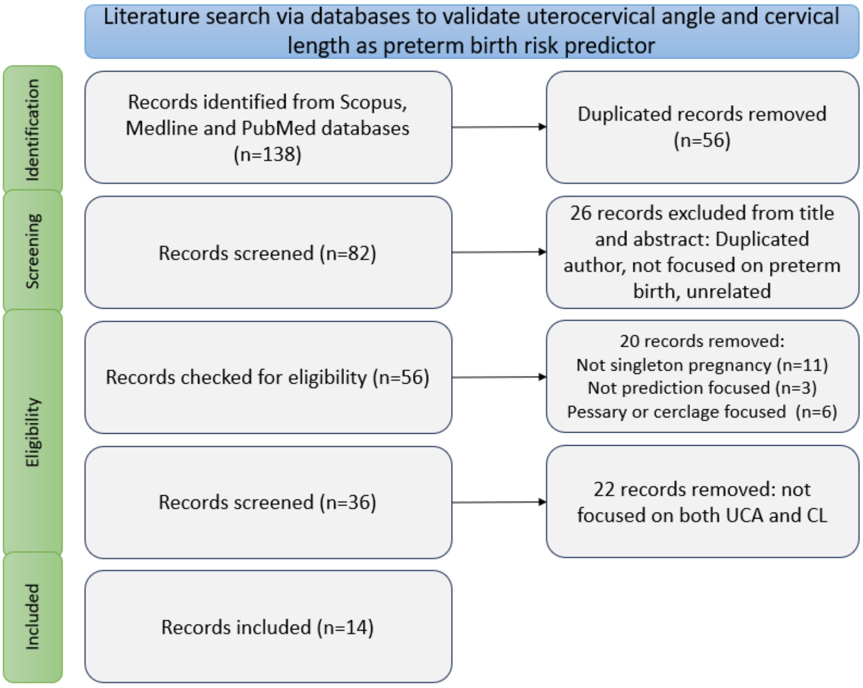

Figure 2: Validity of UCA and CL as preterm birth predictors literature search

Machine learning model for detecting UCA or CL

The keywords used in this search are ‘machine learning’, ‘uterocervical angle’ and ‘cervical length’. Synonyms of keywords are included in the search. Synonyms are also used in the search terms.

Scopus

The initial search term, (TITLE-ABS-KEY("machine learning") OR TITLE-ABS-KEY("object detection")) AND (TITLE-ABS-KEY("uterocervical") OR TITLE-ABS-KEY("cervical length")) AND TITLE-ABS-KEY("calculation"), yielded no results due to a lack of prior research on this specific topic. The search was then broadened to (TITLE-ABS-KEY("machine learning") OR TITLE-ABS-KEY("object detection")) AND (TITLE-ABS-KEY("angle calculation") OR TITLE-ABS-KEY("length calculation")), which returned 25 documents.

Medline via Ovid

The search for machine learning models specifically for UCA and CL calculations returned no results. The terms were then adjusted to focus on using machine learning for general angle and length calculations. Machine learning-related terms returned 290,504 documents, while angle or length calculation terms returned 139 documents. Combining these searches with the Boolean ‘AND’ yielded 9 relevant documents.

# ▲	Searches	Results	Type
1	exp Neural Networks, Computer/ or object detection.mp.	77006	Advanced
2	machine learning.mp. or exp Artificial Intelligence/ or Machine Learning/ or exp Neural Networks, Computer/	287121	Advanced
3	uterocervical.mp.	168	Advanced
4	cervical length.mp. or exp Cervical Length Measurement/	2529	Advanced
5	calculation.mp.	135552	Advanced
6	1 or 2	290504	Advanced
7	3 or 4	2642	Advanced
8	5 and 6 and 7	0	Advanced
9	angle calculation.mp.	88	Advanced
10	length calculation.mp.	51	Advanced
11	9 or 10	139	Advanced
12	1 or 2	290504	Advanced
13	11 and 12	9	Advanced

Figure 3: Literature search for machine learning model for angle and length calculation

PubMed

No results were found specifically for machine learning models to calculate the uterocervical angle and cervical length. The next best search terms used were: ("machine learning" OR "object detection" OR "deep learning" OR "artificial intelligence") AND ("angle calculation"[tiab:~0] OR "length calculation"[tiab:~0]), where [tiab:~0] allows flexible word po sitioning. This search returned 10 results.

A total of 44 records were identified from Scopus, Medline, and PubMed and duplicated records were removed. Titles and abstracts were screened to exclude records with duplicate authors, those not focused on predictions, or unrelated to the project. Further filtering removed non-English and indirectly relevant records, leaving 11 records for analysis. The literature search process is shown below:

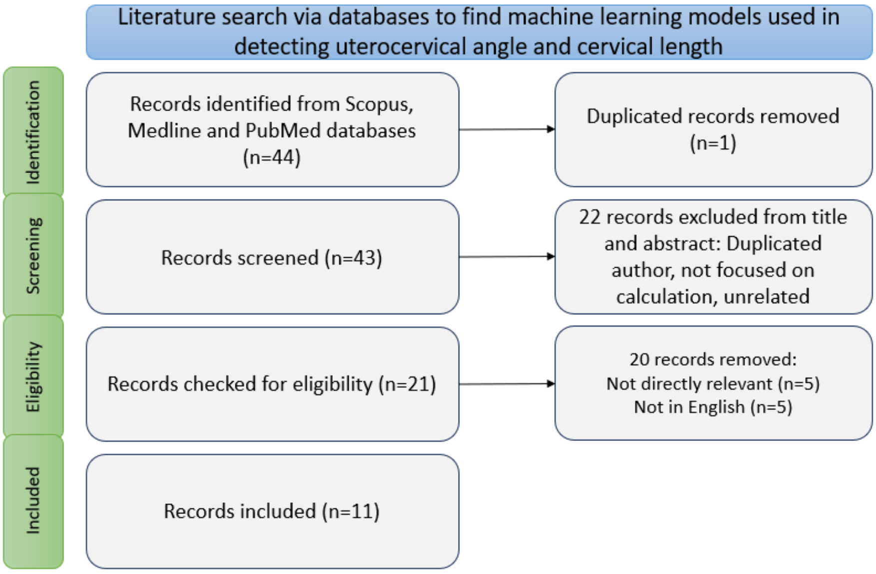

Figure 4: Application of machine learning models for angle and length calculation literature search

Literature Results Review

Uterocervical angle and cervical length as predictor for preterm birth

Numerous studies have examined the validity of using uterocervical angle (UCA) and cervical length (CL) as predictors of preterm birth (PTB) risk, sparking a debate over which is more effective. Traditionally, PTB risk is assessed through transvaginal ultrasound (TUV), with CL being a well-established marker that can be manually measured from TUV images. CL is routinely used to identify high-risk pregnancies so that timely intervention could be provided. [17] In 2016, Dziadosz found a positive correlation between a wider UCA in the second trimester and the risk of spontaneous PTB, initiating interest in UCA as a novel predictor. [19] Recent studies, including those by Pruksanusak and Singh, suggest that UCA may be a stronger predictor than CL, with a significant correlation between an obtuse UCA and spontaneous PTB risk. Pruksanusak also reported higher intra- and interobserver reliability for UCA measurements compared to CL. However, most comparative studies agree that using both UCA and CL together offers better predictive accuracy. Some researchers, like Tanacan and Movahedi, have even developed combined indices, such as the 'combined utero-cervical index (CUCI)' and the angle-cervical length ratio, to enhance prediction accuracy. Both CUCI and the angle-cervical length ratio demonstrate strong performance, with sensitivity ranging from 73% to 78%.

Multiple studies have evaluated the performance of each predictor individually and in combination. The results are compiled in the table below:

Study by	Predictors	P-value	Sensitivity (%)	Specificity (%)	NPV (%)
Luechathananon [18]	UCA≥110.97° CL<3.4 cm	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 [20]	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 [13]	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 [12]	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 [16]	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 [19]	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 clearly demonstrates that combining UCA and CL as predictors significantly improves specificity, meaning the model becomes more accurate at identifying term pregnancies. This improvement is also reflected in the higher Negative Predictive Value (NPV) across studies, indicating a stronger ability to correctly identify term pregnancies. By using both predictors, healthcare providers can more accurately rule out low-risk cases and concentrate on monitoring pregnancies with a higher risk of preterm birth. This proactive approach helps ensure that those most at risk receive focused attention and care, while also saving cost and resources for hospitals.

Machine learning model for detecting UCA or CL

A literature search revealed no previous research specifically using machine learning models to detect UCA or CL. However, by broadening the scope, several studies were identified that apply machine learning models for detecting angles or lengths in general. These studies primarily focus on convolutional neural networks (CNNs), a type of deep learning model. Different CNN architectures have their unique strengths, proving highly effective for identifying, classifying, and measuring objects within images. To train object detection models, a set of training images is provided as input to the model. The training process involves annotating each image by drawing bounding boxes around objects of interest and labelling each box with the corresponding class. Once the model has been trained on this annotated dataset, it can be used to predict objects within a testing dataset, generating bounding boxes around its predictions.

YOLO (You Only Look Once)

The YOLO family of models consists of single-stage networks that perform object detection and bounding box regression in a single pass through a convolutional neural network (CNN). Known for their balance of speed and accuracy, YOLO models are suitable for real-time detection tasks. In studies by Gami, Liu, Pelit, and Wang, different versions of the YOLO algorithm were used. Gamis study used YOLOv3 and reported an impressive average of 98.5% for sensitivity, specificity, accuracy, precision, and F1-scores. [26] Wang introduced an improved YOLO v5 model integrated with a Bidirectional Feature Pyramid Network (BiFPN), which incorporates gamma correction for image preprocessing, improving clarity under varying lighting conditions. This YOLO v5-BiFPN model achieved a minimal error margin of just 3.4% between predicted and actual values, demonstrating its effectiveness in real-world applications. [34] Pelit employed a YOLOv8 model for object detection, achieving success rates exceeding 90% in identifying specific anatomical regions, such as the labrum, ilium, and acetabulum, with an Intersection over Union (IoU) of 0.25. The study concluded that this model is suitable for applications requiring precise localisation of anatomical features. [33]

U-Net

U-Net is a specialized CNN architecture widely used in image segmentation tasks and is capable of classifying pixels to distinguish objects within an image. Jang used this model in their study for knee-ankle angle calculation. [28] U-Net has a U-shaped structure that creates highly detailed segmentation maps using highly limited trading samples. This is important in the medical imaging community, as properly labelled images are often limited. This caused U-Net to have an explosion in usage in medical imaging. [37]

Faster R-CNN

The Faster R-CNN models, as proposed in studies by Li and Zhao, are two-stage detectors that deliver accurate object detection and localisation through a Region Proposal Network (RPN) and bounding box regression. [29][35] Faster R-CNN can be viewed as a combination of RPN and Fast R-CNN. This model demonstrated effectiveness in complex environments and tasks requiring high accuracy. [29] In Zhao's study, a Faster R-CNN model was employed to calculate deformity angles. Their proposed Faster R-CNN model was enhanced with a ResNet50 backbone and a Feature Pyramid Network (FPN). This enhancement added robustness in detecting bone segments in medical images, even in challenging cases with occlusions. The deep layers of ResNet50 facilitate strong feature extraction, while FPN's multi-scale feature fusion allows the model to capture both high-level semantic and low-level spatial details. This combination significantly improves detection accuracy and reliability, particularly for medical applications where complex object structures must be identified. [35] In contrast, Li's study the traditional structure of the Faster R-CNN model to detect objects by generating candidate bounding boxes, refining them through classification, and adjusting positions with bounding box regression. Compared to traditional object detection algorithms, this model improved accuracy by over 30%, showcasing its adaptability and robustness in complex environments. [29] Overall, the Faster R-CNN model, whether enhanced or traditional, remains a reliable choice for tasks that require highly accurate and dependable object detection, especially in medical imaging where precision is critical.

Conclusion

In conclusion, this literature review highlights the importance of the uterocervical angle (UCA) and cervical length (CL) as key predictors for preterm birth. The findings from various studies shows that machine learning models have high potential in the accurate detection and calculation of UCA and CL, thus facilitating the earlier identification of pregnancies at risk for preterm birth. Both UCA and CL have been shown to provide valuable insights into the risk of preterm birth, allowing healthcare providers to implement timely interventions and offer personalised care tailored to at-risk patients. Furthermore, advancements in machine learning techniques not only enhance the accuracy of UCA and CL measurements but also streamline the calculation process, reducing the burden on clinicians. Ultimately, the successful implementation of these innovative methods has the potential to significantly improve maternal and neonatal outcomes by enabling timely interventions for preterm birth prevention.

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