■ RESEARCH ARTICLE

Artificial Intelligence Integrated Fetal Cardiotocography Education Module

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RECEIVED JULY 20, 2022
ACCEPTED AUGUST 28, 2022

CITATION Erdoğan, P., Uyduran, H., Dokuz, Y., Dokuz, A. Ş. & Çakmak. B. (2022). Artificial Intelligence Integrated Fetal Cardiotocography Education Module. *Artificial Intelligence Theory and Applications, 2(*2), 39-50.

Abstract

Cardiotocography (CTG) is an indispensable instrument for assessing fetal well-being at the antenatal period. The interpretation of CTG requires substantial background information, knowledge and experience. In particular, inexperienced clinicians and midwives are easily prone to making mistakes during the evaluation of CTG and wrong decisions. CTG education programs provide remarkable improvements on quality of care. However, limited clinical improvements regarding adverse fetal outcome necessitate new advancements and improvements in educational programs. In this study, it was proposed that adding an immediately available interface for accessing correctly classified real CTG samples would facilitate the learning curve of students. The aim of this study is to develop a new artificial intelligence integrated interface to aid teaching the interpretation of fetal CTG. The parameters of presence of uterine contractions, beat-to-beat variability, fetal heart rate and periodic changes (accelerations and decelerations) of 118 scanned fetal CTGs acquired from Niğde Ömer Halisdemir University, Niğde Research and Training Hospital Obstetrics and Gynecology clinic were classified by 2 experienced obstetrics and gynecology specialists and were uploaded to the interface. Convolutional neural network (CNN) deep learning architecture was used and CTG classification model was generated. The developed interface consisted of 4 sections. First contained the basic information about CTG. Educational information for interpretation of CTG was uploaded to the second section. The third section was designed for students' self-training with randomly selected and previously classified CTGs. The fourth section consisted of a deep learning based trained CTG classification model, for uploading a test sample and generating classification result automatically. The performance of CNN module on the classification of CTG dataset was 84%. In conclusion, artificial intelligence integrated fetal CTG educational interface was successfully developed. Utilization of this new interface contribute great benefit to fetal CTG education for obstetrics and gynecology residents and midwives.

Keywords: cardiotocography, artificial intelligence, convolutional neural network, interface

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Artificial Intelligence Theory and Applications, ISSN: 2757-9778. ISBN: 978-605-69730-2-4 © 2022 University of Bakırçay

1. Introduction

Fetal cardiotocography (CTG) is simultaneous monitorization of fetal heart rate (FHR) and uterine contractions. It is the mainstay of assessment of antenatal fetal well-being since its first introduction in 1960s [1]. CTG is based on the evaluation of FHR changes secondary to uterine contractions and/or fetal movements. CTG is part of routine follow-up both at antenatal period in outpatient settings and at intrapartum period in the delivery room. In the absence of uterine contractions, fetal movements are recorded instead. The FHR reaction in response to fetal movements are recorded for at least 20 minutes and this test is named as Non-Stress Test (NST). In the presence of uterine contractions, on the contrary, the test is named as Contraction Stress Test (CST). Both tests are based on CTG recordings and must be carefully interpreted according to international up-to-date guidelines [2].

Fetal heart rate changes constitute of both short term and long term FHR variability and are strong indicators of fetal cardiovascular system health as well as autonomous nervous system (ANS) integration [3]. In antenatal period fetal ANS is accepted to be fully functional after 32th completed gestational week. Therefore, CTG has wide range of usage beginning at 32nd gestational week up to delivery.

The accurate interpretation of CTG is essential because depending to this interpretation doctors and/or midwives make decisions on the route or timing of delivery and take immediate action. However, the interpretation of the CTG widely differs depending on various factors like gestational age, presence of uterine contractions, the stage of partition if recorded during intrapartum period and systemic maternal or fetal conditions [3]. The major motivation for antepartum and intrapartum fetal monitoring is to prevent fetal hypoxia and acidosis that would end up with fetal death or long-term severe neurologic deficit [4]. FHR monitoring by means of CTG recordings is an important component of fetal assessment. In judicial cases problems in interpretation of CTG remains as a major theme [5]. The most frequent aspects are failure to recognize suspicious and/or pathologic patterns, inadequate timing and/or speed of response to abnormal patterns [5]. In recent British Each Baby Counts program report, risk recognition theme was listed at first place followed by deficiencies in education, interpretation, equipment and inadequate acting [6].

In fact, CTG education is not a routine part of medical faculty curriculum, rather is included in undergraduate and post graduate programs for obstetrics and gynecology residents and midwives. Human interpretation has a long learning curve because interpretation of CTG requires remarkable amount of experience as well as background information [7]. However, theoretical information alone, is insufficient most of the time. Dealing with real patients, real CTGs and real critical situations provide a lot of experience for clinicians. Most of the time clinicians give critical decisions based on not solely theoretical knowledge but also on years of experience [8]. In particular, inexperienced clinicians and midwives are easily prone to making mistakes during the evaluation of CTG and wrong decisions [9, 10].

The cognitive processes of giving critical decisions while dealing with both maternal and fetal health requires a holistic approach. Actually, patients need to be evaluated thoroughly; gestational age, accompanying pathologic conditions, characteristics of previous deliveries are all essential components of final decision. Meanwhile, interpretation of CTG is a major component for clinical decision making. The principal precaution for decreasing stillbirths is better interpretation of CTG and appropriate reaction to recognized abnormal CTG [6]. However, most of the mistakes made during

CTG interpretation are due to human factor [11]. The most frequent human factor involves pattern recognition faults and failure to act timely and/or accurately [8]. Pattern recognition requires remarkable background information. On the other hand, accurate decision making after recognizing the abnormal pattern is another part of the issue and requires both experience and theoretical information.

A review of articles about CTG education reported that especially in survey and test studies remarkable improvement in results was noted [12]. For clinical outcome, on the other hand, the results are conflicting. It has been demonstrated that after compulsory CTG education of the labor staff, quality of care increased while suboptimal care and midwifery mistakes were reduced [13]. Additionally, CTG interpretation skills were improved, interobserver agreement rate was increased and intrapartum CTG was better managed [13]. The authors concluded that CTG education must be compulsory for labor staff [12]. However, organizing both postgrad and undergrad educational sessions is not readily easy. The attendance might be poor and for especially mandatory educations the attendants might be involuntary. For these reasons in the digital era of present time, feasible, convenient and effective programs that people ca n access readily when available are preferred [8]. Another study about on-site training demonstrated that integrating extended on-site training increase inter and intraobserver reliability more than web based education alone [14]. On-site training includes discussions on real cases and integrating different and various learning tools extends its diversity [14].

Previous studies held on CTG education demonstrated the benefits of training at clinic and these programs are part of clinic education programs [12]. However, limited clinical improvements regarding adverse fetal outcome necessitate new advancements and improvements in educational programs. In this study, it was proposed that adding an immediately available interface for accessing correctly classified real CTG samples would facilitate the learning curve of students. Therefore, the aim of this study is to develop a new artificial intelligence (AI) integrated interface to aid teaching the interpretation of fetal CTG.

2. Materials and Methods

The study was held in Niğde Ömer Halisdemir University Education and Research Hospital Obstetrics and Gynecology Clinic. CTG traces recorded and printed between 01 January 2022 and 01 March 2022 were scanned and saved in png format.

CTG traces with intervals 2cm/minute and recorded with both probes attached in patients after completed 32 gestational weeks were included in the study. CTGs that had absent data for more than 5 minutes in total, were shorter than 20 minutes, had either FHR or contraction probe unattached were excluded. CTGs were interpreted by 2 experienced obstetrics and gynecology specialists using FIGO (International Federation of Gynecology and Obstetrics) 2015 guidelines.

The parameters recorded were presence of uterine contractions, beat-to-beat variability, baseline fetal heart rate and periodic changes (accelerations and decelerations). Fetal heart rate was estimated in time period of at least 10 minutes and was expressed as beat per minute (bpm). Baseline FHR was accepted as normal if between 110-160 bpm, tachycardia if above 160 bpm and bradycardia if below 110 bpm. For each CTG sample the baseline FHR was determined, recorded and a black color line was drawn representing the estimated basal FHR. Variability refers to the oscillations of FHR occurring in 1minute time period. Normal variability refers to oscillation amplitude of 5-25 bpm. If oscillation amplitude was below 5 bpm, the CTG was marked as decreased variability and if oscillation amplitude was above 25 bpm, it was marked as increased variability. In all CTG samples the determined variability was marked by a black ellipsoid so that students can calculate the variability themselves. For periodic changes accelerations and decelerations were detected. Accelerations were FHR increments of 15 bpm or more, lasting at least 15 seconds, but no more than 10 minutes. Decelerations were FHR decrements of 15 bpm or more, lasting at least 15 seconds, but no more than 10 minutes. Accelerations were marked by red ellipsoid; decelerations were marked by dark blue ellipsoid. Contractions were considered present when a bell-shaped gradual increase in uterine activity, lasting average of 45-120 seconds, followed by a similar gradual decrease reaching the baseline uterine activity was detected. They were marked by black arrows. Fetal movements were assumed to be present when a sudden peak occurs followed by immediate return to baseline uterine activity. These were marked by red arrows. Following the interpretation, the CTGs were uploaded to the interface.

For the deep learning module of the interface Convolutional Neural Network (CNN) deep learning architecture was used and CTG classification model was generated. YOLO v4 is selected for pre-trained object detection neural network architecture which was proposed in 2020 [15]. The main advantage of YOLO v4 over previous YOLO models is that it has the optimum performance based on both detection accuracy and speed [15]. Three main parts consist in YOLO v4; namely backbone, neck, and prediction. YOLO v4 is applied to many application domains, such as face mask wearing detection [16, 17], flower detection [18], traffic sign recognition [19, 20], and lesion detection [21, 22].

In this study, YOLO v4 is applied on CTG images to determine whether the image contains one of the contraction, acceleration, or deceleration. The parameters of YOLO v4 model for CTG classification is presented in Table 1.

These parameters are obtained by trial-and-error approach with different parameter values. The main steps of the proposed deep learning module are presented in Algorithm 1. The collection and labelling of the dataset and application of CNN on the prepared dataset shows the applicability of the proposed method on CTG classification.

Table 1. The utilized parameters of YOLO v4 for CTG classification

Parameter	**Value**
Input Size	416 x 416
Learning Rate	0.001
Batch Size	64
Classes	3
Iterations	3000

Algorithm 1. Steps of proposed CTG classification module
Step 1. The CTGs are collected and scanned as images to the computer. Step 2. The CTG images are preprocessed and classified. Step 3. The CTG images are labelled. Step 4. YOLO v4 is applied on the labelled CTG images. Step 5. The results of YOLO v4 is evaluated.

As can be seen in Algorithm 1, first, the CTG records are scanned as images into the computer. Second, The CTG images are preprocessed and classified based on their classes. Third, the CTG images are labelled using an image labelling program. Fourth, YOLO v4 model is applied on the labelled and classified training dataset. Finally, fifth, the performance of YOLO v4 model is evaluated.

3. Results

In total 118 CTG samples were collected. The interface was developed in both Turkish and English languages and was named as NST-I. 98 of the total CTG samples are used as training set, and 20 of the CTG samples are selected as test set, randomly.

It consisted of a main page and 4 connecting modules (Figure 1). First module was named as "What is NST?". It is a simple educational section, compromising of 16 pages of background information for explaining the logic, mechanism and workflow of CTG recording.

Figure 1. Main page and four connecting modules of the program.

Second module was named as "NST education". It is a detailed education section. It consisted of 89 pages describing in detail the technique and most up-to date guidelines (FIGO 2015) for interpreting CTG traces. The information in first 2 sections were quantitatively and qualitatively identical to theoretical education of undergraduate midwifes and obstetrics and gynecology residents in our university. Both lectures were given by the authors.

Third section was named as “NST test” (Figure 2). In this section by pressing the begin test button, a random generator chooses a previously classified and uploaded CTG sample and project it to the screen. The student can examine the image for the 3 main aspects. For variability there were 3 choices as increased, decreased or normal variability. After the students selects the choice, the program marks the answer as correct or incorrect. For basal heart rate 3 choices were present as tachycardia, bradycardia and normal. After student marks his/her answer, the program marks it as correct or incorrect and also reflects the previously determined basal heart rate value on the screen. For uterine contractions and periodic changes, after the examination the students press the button and previously marked results appear on the screen. When correct option was selected the previously marked variability, basal heart rate, periodic changes, fetal movements or uterine contractions appear on the image (Figure 3).

Figure 2. Third module of the program consists of a random generator for previously classified CTG samples

Figure 3. Previously marked results appear on the screen after the correct answers were chosen.

Fourth module was named as NST scanner (Figure 4). In the fourth module, CNN based YOLO v4 deep learning object detection model was used. In this module, the student uploads an image of CTG and YOLO v4 model detects contractions, accelerations, and decelerations. By pressing the button of “Contraction” the system shows the contractions of the uploaded CTG image which was detected by the deep learning model. Similarly, by pressing “Acceleration/Deceleration” button, the system shows the accelerations and decelerations which were detected by the deep learning model. The performance of the YOLO v4 model on classification of CTG in terms of contraction, acceleration, or deceleration is presented in Figure 5. As can be seen in the figure, the loss of the model has converged after 2000 epoch and the final loss value is 0.28 after 3000 epoch. The mean Average Precision (mAP) value is observed as 84% which shows that the YOLO v4 based CTG classification model has reliable performance.

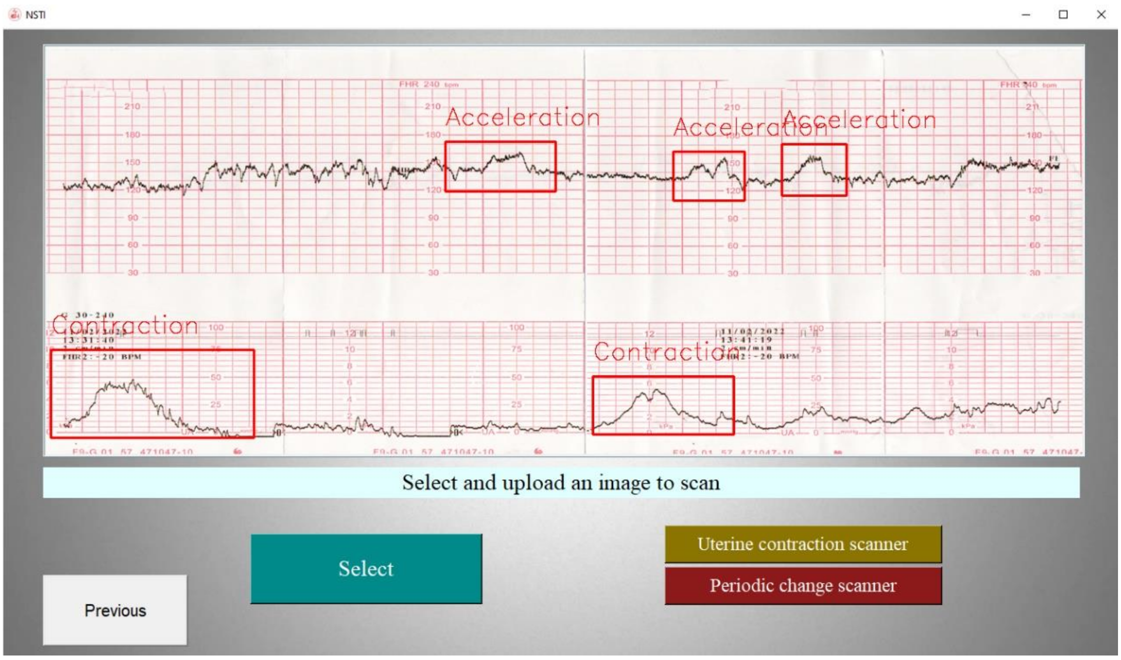

Figure 4. Fourth module of the program scans and automatically classifies the CTG by using deep learning architecture.

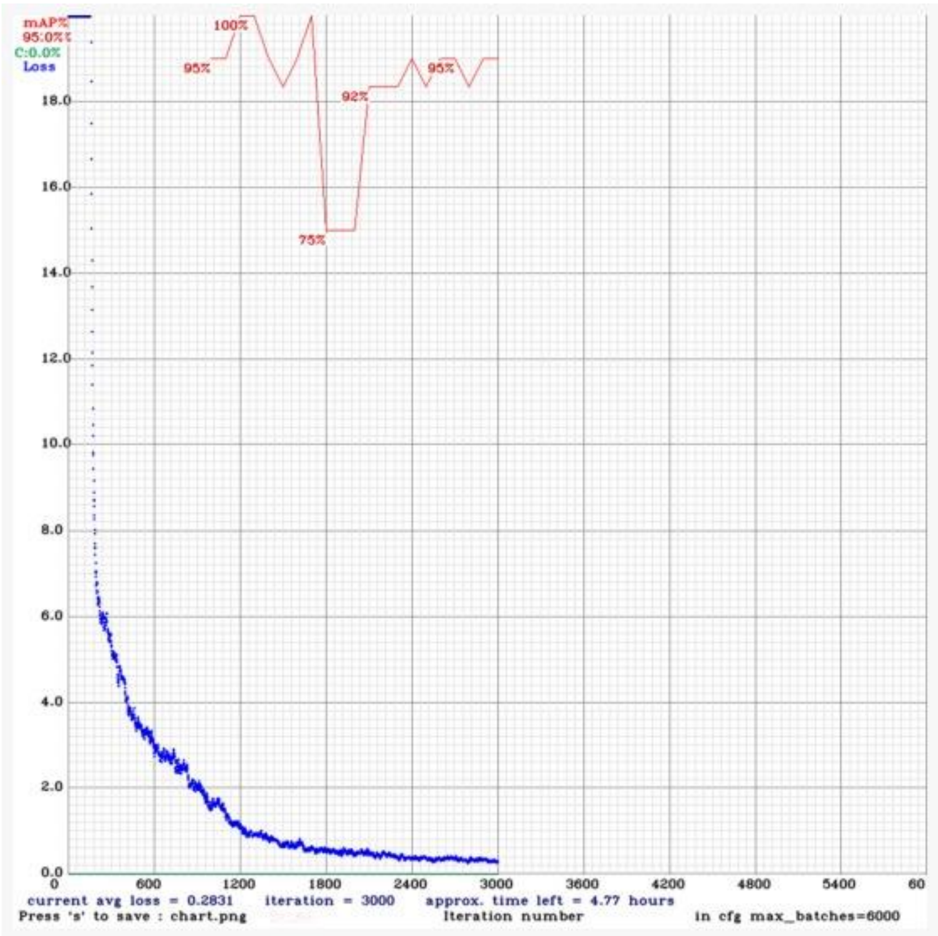

Figure 5. The performance of YOLO v4 based CTG classification model

4. Discussion

This project resulted in development of a 4 staged, AI integrated CTG education interface. The target population of this module were obstetrics and gynecology residents and midwives, as part of their postgraduate in-clinic education programs.

Periodically up-dated guidelines are used for pattern recognition and accurate interpretation of CTG [3]. However, both learning and staying up –to date for these criteria is difficult because learning curve is long. Recent reports demonstrate that considerable amount of inter and intraobserver variations were detected even among experienced clinicians while evaluating CTG based on FIGO 2015 criteria [1, 23, 24]. Therefore, seeking methods for eliminating or minimizing human errors were focus of recent research. These research were generally 2 armed. Some researchers concentrated on adequately educating both undergraduates and postgraduates for accurate interpretation of CTG [8, 10, 12, 14, 25]. Some other researchers, on the other hand, claim human pattern recognition would always be deficient and propose computer aided systems alerting staff in case of abnormal CTG to be integrated as a part of routine care [26–31].

The role of applied CTG interpretation education of delivery room staff has been clearly established. [8]. Inappropriate theoretical and practical education results in unnecessary caesarean section rates as well as fetal compromise due to preventable asphyxia [8]. Confidential Enquiry Report recommend regular education for obstetricians and midwives [8, 32]. Accordingly, in 2000 Beckley introduced their computer based program for CTG education. This preliminary model consisted of 2 sections of educational material. In total acid-base equilibrium education of 2-4 hours and CTG evaluation education of 1-2 hours. Using this program provided better education of the staff [8]. Later on, Thellesen et al., introduced a national CTG educational program in accordance with Delphi agreement in 2015 [10]. In the following years, studies on clinical utilization of this program was also published [9, 33]. In the latest article results of compulsory CTG education of midwives and doctors in Denmark were reported [33]. This education resulted in a transitional increase in emergency caesarean section rate and a 14% reduction in assisted vaginal deliveries, but no reduction of fetal hypoxia risk, in 331282 vaginal deliveries in Denmark [33]. No changes in neonatal outcomes (Apgar score, cord pH, admittance to a neonatal unit) were observed after training. This was mainly attributed to very low prevalence of adverse neonatal outcome by the authors [33].

Thus far, although various educational modules were developed for fetal CTG training, CNN integration was not performed before. Fetal CTG training with utilization of AI would improve educational outcomes.

There are many studies on different science fields demonstrating that computed based educational programs enhance the efficiency of conventional education [8]. This study presents a web-based AI integrated education system for the first time. It was developed for students at the first place however, can easily be adopted for postgrad and in-company training programs. It can be accessed any time, can be exploited without time and access limit. Additionally, real CTG samples, classified and marked by experts according to FIGO 2015 were substitutes for on-site learning. The number of these samples can be increased by time. Besides, a CNN based AI module is integrated to the presented program which enables trainees to scan and interrogate with any CTG. AI recognize the presence of uterine contractions, accelerations and decelerations with 84% accuracy. This is not a simple web-based or e-learning computer program. The most striking part of this newly introduced interface is the fourth module which consisted a deep learning based program. It is trained to recognize pattern. Therefore, this system can be utilized at any time easily without time loss and before oblivion of acquired theoretical and practical skills. Because it has been shown that the effectiveness of theoretical information lasts for 6-7 months [8]. After this period of time repetitive lessons are necessary or else the acquired information and skills are forgotten. Besides, accurate CTG interpretation is a complicated, sophisticated clinical skill and is directed by international guidelines. These guidelines are periodically up-dated. Therefore, staff dealing with target population needs to consolidate acquired knowledge and skill periodically as well as should update their information according to international guidelines. Moreover, the utilization time and duration can be individualized according to the pre education knowledge of the trainee. Especially staff with pre education low performance would take more time in the program. Accordingly, in another study midwifes had worse performance than doctors in pretest applied before the teaching program, however after the education the difference disappeared [25].

The second arm of research was computer aided diagnosis (CAD) for intrapartum simultaneous machine interpretation. CAD methods were used in clinic for many years now, available studies demonstrate that they are not enough in improving fetal outcome [34] . The main reason is that when an abnormal CTG is present, the damage is already done most of the time. Five trademarks are available. Because they are trade products, not detailed information is available on the operant programs. Subsequently, some machine learning (ML) algorithms were developed [26, 35]. More recently deep learning was introduced for decision making in CTG evaluation [29]. CNN and Recurrent neural network (RNN) based deep learning eliminated errors caused by pattern recognition defects. Tang et al. compared ML models with Artificial neural network (ANN) models including CNN and RNN. They found CNN classification methods had better performance.

It is important to note that if same pattern recognition is used like FIGO 2015 guidelines, same errors are prone to be made even with ML algorithms. ML algorithms eliminate human factor but intrinsic errors caused by pattern recognition remains. CNN based deep learning directly learns but requires big data. Data in this study is limited, and therefore only major themes like presence of contractions, accelerations and decelerations were trained. However, decelerations have many subheadings and depending on the duration, association with the timing of contraction decelerations may vary from harmless to severely detrimental. Therefore, clinically useful deep learning tool needs to be reconstructed with hundreds more real scanned CTG.

Starting from the previous studies on this field, an educational module was designed. The originality of this work was integration of CNN based AI for pattern recognition. The contribution of this study to the scientific era is evolution of CTG education towards distance, on-line and AI integrated version. This would imply individualized and therefore more efficient education of individuals. The main limitation of this study is that a preliminary model was developed and only a limited number of CTG was used to train the AI. Further research by means of increasing the number of CTG samples for training AI, would increase the accuracy rate. Additionally, and probably, the discrimination between early, late and variable decelerations would be possible by increasing the data. Finally, the authors argue that integrating real and accurate classified CTG samples by means of a feasible, convenient and easily accessible interface would highly improve the adaptation and motivation of students. This interface would increase the self-confidence of students as well as the rate of accurate classification. Moreover, integration of AI to the interface would further enhance the accuracy of critical decision making in both education eras and in clinic.

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Abbreviation List

Fetal cardiotocography (CTG)

Fetal heart rate (FHR)

Non-Stress Test (NST)

Contraction Stress Test (CST)

Autonomous nervous system (ANS)

Artificial intelligence (AI)

International Federation of Gynecology and Obstetrics (FIGO)

beat per minute (bpm)

Convolutional Neural Network (CNN)

mean Average Precision (mAP)

Computer aided diagnosis (CAD)

Machine learning (ML)

Recurrent neural network (RNN)

Artificial neural network (ANN)