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Ghi Tullio (Orcid ID: 0000-0003-1823-1096)
Conversano Francesco (Orcid ID: 0000-0002-9537-8334)
Ramirez Zegarra Ruben (Orcid ID: 0000-0001-7706-3016)
Dall'Asta Andrea (Orcid ID: 0000-0001-7201-0206)
Lau Wai-lam (Orcid ID: 0000-0001-9636-704X)
Iliescu Dominic (Orcid ID: 0000-0002-7823-3387)
Rizzo Giuseppe (Orcid ID: 0000-0002-5525-4353)

A novel artificial intelligence approach for the automatic differentiation of fetal occiput anterior and non-occiput anterior positions during labor

T. Ghi[1*], F. Conversano[2*], R. Ramirez Zegarra[1,3], P. Pisani[2], A. Dall´Asta[1], A. Lanzone[4], W. Lau[5], A. Vimercati[6], D. G. Iliescu[7,8] I. Mappa[9], G. Rizzo[9,10], S. Casciaro[2], on behalf of the International Study Group on Labor and Delivery Sonography (ISLANDS)#

[1] Department of Medicine and Surgery, Obstetrics and Gynecology Unit, University of Parma, Parma, Italy

[2] National Research Council, Institute of Clinical Physiology, Lecce, Italy

[3] Department of Obstetrics and Gynecology, St. Joseph Krankenhaus, Berlin, Germany

[4] Obstetrics and High-Risk Unit, Fondazione Policlinico A. Gemelli IRCCS, Rome, Italy

[5] Department of Obstetrics and Gynecology, Kwong Wah Hospital, Kowloon, Hong Kong

[6] Department of Obstetrics, Gynecology, Neonatology and Anesthesiology, University Hospital of Bari Consorziale Policlinico, Bari, Italy

[7] University Emergency County Hospital Craiova, Romania

[8] University of Medicine and Pharmacy Craiova, Romania

[9] Division of Maternal and Fetal Medicine, Cristo Re Hospital, University of Rome Tor Vergata, Rome, Italy

[10] Department of Obstetrics and Gynecology, The First I.M. Sechenov Moscow State Medical University, Moscow, Russia

*****T. Ghi and F. Conversano contributed equally to this work

#Collaborators are listed in supplementary materials

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Corresponding Author:

Prof. T. Ghi, MD, PhD

Department of Medicine and Surgery, Obstetrics and Gynecology Unit, University of Parma
Address: Viale A. Gramsci 14, 43126 Parma, Italy
E-mail: tullioghi@yahoo.com

Contribution

What are the novel findings of this work?

A newly developed Machine Learning based algorithm for the automatic assessment of the fetal occiput position at transperineal ultrasound can accurately differentiate between occiput anterior and non-occiput anterior positions.

What are the clinical implications of this work?

The addition of a fast AI-based algorithm, which could perform an efficient automatic classification of the sonographic images and reliably assess the fetal head position, might have a place in the labor ward and could also be trained to assess at once both the fetal position and the station on the same scanning plane.

ABSTRACT

Objectives:

The aim of this study is to develop a Machine Learning (ML) algorithm for an automatic classification of fetal occiput position at transperineal ultrasound (TPU) during the second stage of labor.

Methods:

Prospective cohort study including singleton term pregnancies (> 37 weeks of gestation) in the second stage of labor, with the fetus in cephalic presentation. Transabdominal ultrasound was preliminarily performed to assess the actual fetal occiput position, which was labeled as occiput anterior (OA) or non-occiput anterior (non-OA). Subsequently, for each case, one sonographic image of the fetal head was acquired on the axial plane using TPU and archived on a cloud for remote analysis. Using the transabdominal sonographic diagnosis as the gold standard, a ML algorithm based on a pattern recognition feed-forward neural network was trained on the transperineal images to discriminate between OA and non-OA cases. In the training phase the model tuned its parameters in order to approximate correctly the training data – i.e., the training dataset – in order to correctly assess the fetal head position, by exploiting geometric, morphological and intensity-based features of the images. In the testing phase, the diagnostic performance of the algorithm was evaluated on unlabeled data, which represented the testing dataset. On this group the ability of the ML algorithm to differentiate the OA from the non-OA fetal positions was assessed in terms of diagnostic accuracy. The F_1-score and Precision-Recall Area Under the Curve (PR-AUC) were also calculated to assess the algorithm's performance. The Cohen's kappa (*k*) was finally added to evaluate the agreement between the algorithm and the gold standard.

Results:

Over a period of 24 months, 1219 women in the second stage of labor were enrolled. They were classified as OA (n=801 or 65.7%) or non-OA (n=418 or 34.3%) on the basis of transabdominal

ultrasound. From both the sub-groups (OA and non-OA), 70% of the patients were randomly assigned to the training dataset (824 patients) while the remaining 30% (395 patients) were used as testing dataset.

On the latter group the ML based algorithm yielded a correct classification of the fetal occiput position in 90.6% of cases (357 out of 395), including 224 out of 246 OA (91.0%) and of 133 out of 149 non-OA images (89.3%). Moreover, for the evaluation the algorithm's performance we found a F_1-score=88.7% and PR-AUC=85.4%. The algorithm showed a balanced performance in the recognition of both anterior and non-anterior occiput positions. Eventually, the robustness of the proposed algorithm was confirmed by a high agreement with the gold standard method ($k = 0.81$; $p < 0.0001$).

Conclusion:

A ML-based algorithm for the automatic assessment of the fetal head position at TPU has been developed and can accurately differentiate between OA and non-OA positions. This algorithm has the potential to support not only obstetricians, but also midwives and accoucheurs in the clinical use of TPU.

INTRODUCTION

The ascertainment of the fetal occiput position using intrapartum ultrasound has recently gained popularity as a complementary tool to the traditional transvaginal digital examination (1). The knowledge of the fetal occiput position is of major relevance in the management of protracted labor, as malposition of the fetal head is associated with an increased risk of obstetric intervention, failed operative vaginal delivery, and adverse maternal or perinatal outcomes (2-8).

The assessment of the fetal occiput position using transabdominal ultrasound has been demonstrated to be more objective and reproducible than traditional digital examination alone, which is associated with a mean rate of error of 20% or even higher (up to 70%) in cases of occiput posterior or transverse (9-11). Therefore, the sonographic ascertainment of the fetal occiput position before considering or performing an instrumental vaginal birth has been recently endorsed by clinical and labor ultrasound guidelines, particularly in those cases where the actual position of the fetal occiput is uncertain following clinical examination (12-15). For this aim, transabdominal ultrasound is considered the preferred method to accurately determine the fetal occiput position during labor (12-28). However, the diagnosis of the fetal head position is feasible also at transperineal ultrasound (TPU), which represents the standard method to assess the fetal head station during labor (29). Ideally, the use of transperineal scanning to assess simultaneously the fetal station and position would be desirable, but in fact, the sonographic diagnosis of the fetal occiput position by TPU is technically challenging for non-experienced operators (29).

The use of Artificial Intelligence (AI) techniques has been recently introduced in obstetrics and gynecology with the aim to provide fast and automatic recognition and measurement of normal and abnormal ultrasound findings (30-37). However, to our knowledge, no study has attempted to assess the fetal occiput position during labor using an AI-based model. In this study, we describe a newly developed Machine Learning (ML) algorithm, based on a pattern recognition feed-forward neural network, for the automatic recognition of fetal head position at TPU and describe its performance in the differentiation between OA and non-OA position during the second stage of labor.

MATERIAL AND METHODS

This study was conducted within the framework of the prospective cohort study known as "AI OCCIPUT" International Multicenter Clinical Study promoted by the University of Parma. The following 15 Maternity Hospitals, all affiliated to the International Study Group on Labor and Delivery Sonography (ISLANDS), contributed to the collection of the clinical dataset evaluated in the present work: University Hospital of Parma (Italy), East Suffolk and North Essex Foundation Trust (ESNEFT, England), Policlinico Gemelli (Rome, Italy), Kwong Wah Hospital (Hong Kong), Ospedale Cristo Re Tor Vergata University (Rome, Italy), University County Hospital Craiova (Romania), University Hospital of Bari (Italy), Trondheim Hospital (Norway), Mangiagalli Hospital (Milan, Italy), Kaplan Medical Center (Israel), Kwame Nkrumah University (Ghana), Woman's Clinic Lucerne (Switzerland), Medias Municipal Hospital (Romania), Charité University Hospital (Berlin, Germany), Imperial College Healthcare NHS Trust (London, England). The study was approved by the ethics committee of the promoting center (270/2018/OSS/AOUPR) and by the local ethics committees of each participating unit.

A non-consecutive series of uncomplicated singleton term pregnancies (> 37 weeks of gestation) in the second stage of labor, with non-anomalous fetuses in cephalic presentation were considered eligible for the study. Women were approached after their admission to the labor ward and written consent was obtained prior to enrolment for the anonymized use of the images to train and test the ML algorithm. The images were obtained by the attending obstetricians on the basis of a locally validated clinical indication, such as protracted labor, vaginal bleeding, non-reassuring cardiotocography (CTG) findings, or before performing an operative vaginal delivery. No TPU was performed in addition to the standard care of the collaborating centers.

Ultrasound assessment

All the recruited patients were preliminarily submitted to transabdominal ultrasound to assess the actual fetal head position. This was considered as the gold standard for the diagnosis of occiput position, and on this basis the fetal position was labeled as occiput anterior (OA) or non-occiput anterior (non-OA). At transabdominal ultrasound the fetal occiput position was described using a clock as a reference as previously suggested (17,25): positions ≥ 02.30 h and ≤ 09.30 h were recorded as non-OA, and positions > 09.30 h and < 02.30 h as OA.

Immediately after the transabdominal scan, for each case, one single image of the fetal head was acquired on the axial plane using TPU.

Transperineal scan was performed using conventional ultrasound, with the following settings: convex probe with 65 mm radius of curvature, field of view 60°, nominal central frequency 3MHz (band from 2 to 5 MHz), scan depth 180 mm, multi-focused image with at least 2 focuses (1st at about 30-50 mm, 2nd at about 100-150 mm) and linear Time Gain Control (TCG). The acquisition of the images was accomplished as a standard B-Mode image (PNG or BITMAP format with at least 512 x 512 pixels).

All the acquisitions were performed using either a generic ultrasound machine manually set in accordance with the above-mentioned parameters or the SensUS Touch system (Amolab Srl, Lecce, Italy), a tablet-like portable ultrasound system equipped with a software module specifically dedicated to the “AI OCCIPUT” study, which automatically ensured the adoption of all the acquisition parameters mentioned above and the capture of images having the prescribed resolution and format requirements.

Each acquisition was performed with the woman lying in a semi-recumbent position, with the legs flexed at the hips and knees at 45° and 90°, respectively. The probe was transversally placed over the posterior fourchette, with the operator exerting a firm pressure but without creating discomfort to the patient. The transducer was angled until the skull contour appeared as clear as possible and the midline was clearly visible, indicating that the ultrasound beam was perpendicular to the fetal skull.

The sonographic image acquired transperineally for each patient was archived on a cloud for remote analysis.

The images underwent offline quality assessment by the Italian National Research Council's (CNR) researchers who carefully verified that each image had been acquired according to the prescribed parameter settings (e.g., depth, focus, aperture angle, etc.), and manually excluded the ones who did not meet the criteria.

Algorithm architecture and training

The algorithm architecture consisted of an initial phase of image preprocessing, followed by data augmentation, feature extraction and the training/testing phases, based on a supervised learning approach (Figure 1).

In the pre-processing phase, the images were normalized and resized to 512x512 pixels and the gray level image histogram was optimized to enhance the contrast and facilitate the detection of the sonographic markers of occiput position (e.g., convergent choroid plexus, moulding; Figure 2a).

The whole dataset of transperineally acquired images was split into a train dataset (70% of total images) and test dataset (30% of total images), by randomly selecting images from OA and non-OA cases, which had been previously classified as such by transabdominal ultrasound.

Subsequently, we applied a data augmentation technique to increase the training dataset amount and to enhance the model performance. Our data augmentation strategy was based on flipping (horizontal), geometric transformations (rotation and translation), noise injection (Gaussian and Speckle) and contrast distortion. Therefore, each image in the original dataset underwent six transformations, whose parameters (for example rotation angle or the Gaussian filter standard deviation) were randomly chosen, resulting in a training dataset of 4944 images.

In the following phase, the algorithm extracted automatically specific morphologic features of the images in order to assess the fetal head position, as detailed below:

a. Ellipsoid segmentation and measurement of the length of the major (A), i.e. the *brain midline*, and minor (B) axes (Figure 2b).

b. A further adjustment of the gray levels was applied to evaluate the thickness of bone interfaces (C and D; Figure 2c).

c. Measurement of geometric characteristics calculated on the gray levels with respect to the intersection of the axes: position of the center of gravity of the grays (M), position of the darkest (*orange*) and lightest (*green*) areas close to the vertical axes, etc. (Figure 2d).

Moreover, the algorithm was designed to extract features related to image texture and structure, as reported below:

a. Texture recognition with histogram of oriented gradients.

b. Second order statistical texture feature recognition with level co-occurrence matrix.

c. Texture homogeneity through inverse difference moment.

d. Image uniformity through energy calculation.

e. Individuation of grey levels of neighboring pixels with correlation.

f. Shape recognition with auto-regressive model.

The feature extraction step transformed each preprocessed image in a vector, where each element corresponded to a feature, representing the input data to feed the classifier network.

A pattern recognition feed forward network with 12 hidden layers was used to classify data. The network training was optimized through gradient descent with adaptive learning rate backpropagation (initial learning rate was 0.001), cross-entropy was used as loss function, Rectified Linear Unit (ReLU) as activation function. A softmax classifier was used as output layer.

The ML algorithm was trained and validated on the augmented training dataset through k-fold cross-validation: the train dataset was partitioned into k sub-groups, or folds, and the algorithm was trained on k-1 folds and validated on the remaining fold, iterating the process k times. In this work, the parameter k was set equal to 5 (38).

Following the training phase, the testing phase was carried out with the remaining 30% of the TPU images – i.e., testing dataset –. In the analysis of each case, the system was blinded to the actual occiput position labeled at transabdominal ultrasound. Using this approach, we evaluated the diagnostic performance of the algorithm in distinguishing the OA from the non-OA positions.

Data analysis was performed on a laptop equipped with an Intel i7 Core™ i7-3610QM processor at 2.3GHz (8GB of RAM, 64 bits).

Statistical analysis

In order to assess the algorithm performance for the training and for the classification of OA and non-OA images, the accuracy was calculated, within each group, as the ratio of correct predictions to the total number of considered images.

The overall accuracy was also calculated as described above, by considering OA and non-OA groups together.

Due to the unbalanced numbers of OA and non-OA classes, the F_1-score and the Precision-Recall Area Under the Curve (PR-AUC) were also evaluated as a measure of the algorithm performance (39).

Moreover, the Cohen's kappa was calculated to measure the degree of the agreement between the ML-algorithm and the gold standard. The significance level was set at p-value < 0.05.

The sample size was calculated through preliminary simulations of the algorithm's training phase, which were performed to assess the minimum sample size for avoiding both overtraining and undertraining of the neural network. The minimum required sample size for the training of our model was about 700 data samples (i.e. 700 images), which, taking into account that we had to dedicate 30% of all the acquired images to the independent testing dataset, finally resulted in a minimum required sample size of about 1000 images.

RESULTS

Over a period of 24 months, 1635 transperineal images of labouring women were collected, of whom 416 did not comply with the prescribed parameter settings and were excluded. Therefore, 1219 transperineal images were included for analysis (Figure 3). The list of the 15 participating centers and their relative contribution to the final sample size are shown on Table 1.

The TPU images were labeled as OA (n=801 or 65.7%) or non-OA (n=418 or 34.3%) on the basis of transabdominal ultrasound findings. From the original pool of both OA and non-OA subgroups, 70% of the images were randomly selected to form the training dataset (n=824), while the remaining 30% of the images (n=395) was used for the testing phase. The "testing dataset" was composed of 246 OA images (62.3%) and of 149 non-OA images (37.7%).

The overall accuracy of the AI-based algorithm in the assessment of the fetal head position on the testing dataset was 90.6% (357/395). The performance of the algorithm in each subgroup was also evaluated. For the OA group, the accuracy was 91.0% (224/246), and for the non-OA group was 89.3% (133/149).

The performance of the algorithm was evaluated also through the F_1-score, which resulted equal to 88.0%, while the PR-AUC was 85.4%. The ML-algorithm also showed a good agreement with the gold standard (k = 0.81, p < 0.0001).

The assessment of the fetal occiput position of each image by the ML-algorithm was achieved in approximately 390 milliseconds.

DISCUSSION

Main findings

The transperineal sonographic diagnosis of the fetal occiput position during the second stage of labor is achievable by means of a ML based algorithm with an overall accuracy of 90.6%. Moreover, the ML based algorithm achieved an equivalent level of precision in the diagnosis of OA (91.0%) and non-OA (89.3%) fetal head positions.

Interpretation of the findings

The present study has provided original data on a model of ML-algorithm that is able to automatically differentiate an OA from a non-OA position using TPU.

The correct diagnosis of fetal head position using transvaginal digital examination has been proven to be highly inaccurate even among experienced obstetricians (9-11). On this basis, the use of transabdominal ultrasound to confirm the fetal occiput position, especially before performing an operative vaginal delivery, has been recommended as the gold standard by some professional societies (12-15). Transperineal ultrasound scanning for the assessment of the fetal head position has also been described to be feasible and accurate (29) although this approach is mainly used to assess the fetal head station and rotation during labor (40-42). Ideally, the use of transperineal scanning to assess simultaneously the fetal station and position would be preferable to save time when fast clinical decisions are needed, especially when considering an instrumental vaginal delivery in the advanced second stage of labor. A transperineal approach would provide an integrated evaluation of the fetal head position and station, especially when the head is deeply engaged below the infrapubic level, where a view of the entire fetal head contour and its landmarks might be more comprehensive than at transabdominal approach, which could be obstructed by shadowing cast by the pubic bone.

Nonetheless, the transperineal sonographic diagnosis of fetal head position can be challenging for operators who are not experienced in fetal brain imaging, which is mainly the case for the obstetricians working in the labor ward. A good knowledge of the shape and morphology of the internal brain structures (such as choroid plexus, cerebellum, thalami) has been actually suggested to be necessary for recognizing the fetal occiput position at TPU (29). On this basis, the use of a ML trained algorithm for the automatic diagnosis of the fetal head position is expected to overcome the issue posed by the subjective interpretation of the transperineal sonographic findings.

Clinical implications and future perspectives

The knowledge of the fetal occiput position is of major relevance in the management of protracted labor, because malposition is strongly associated with an increased risk of cesarean delivery, failed operative vaginal delivery and adverse maternal and fetal outcomes (5). Therefore, the introduction of a fast AI-based algorithm, which could reliably assess the fetal head position at TP US, might have a place in the labor ward daily practice.

Furthermore, a ML algorithm could also be trained to assess simultaneously both the fetal position and the station on the same scanning plane at axial TPU. It has been already described that the automatic measurement of the HPD using a dedicated software is feasible and accurate (43,44). We, therefore, strongly believe that the greatest clinical benefit of a diagnostic ML model for the assessment of the fetal head position would be in hands of non-expert examiners.

Previous studies

While our work is unprecedented in the use of AI technology for labor ultrasound, one study has previously explored the use of AI technology on fetal head biometry using 3D volumes, and shown a high level of agreement between experienced operators and the AI-software for the measurements of biparietal diameter and head circumference (34). Other studies, even without the employment of AI, have focused their attention on the automatic measurement of TPU parameters, such as AoP and HPD (43-47).

To the best of our knowledge, this study is the first designed to use an AI-based algorithm combined with TPU to assess the fetal head position.

Strengths and limitations

The multicentric, prospective and original design of the study, the large number of images obtained, and the reliability of the manual analysis of the images, performed by experienced sonographers in the field of TPU, are among the main strengths of this work.

There are also some limitations that must be acknowledged. First, the study was performed on an offline basis. Therefore, before introducing this tool in the routine clinical practice, a validation study in a real clinical scenario with real-time patients is mandatory. Second, our recruitment was non-consecutive, which could have potentially introduced selection bias. Third, the total number of excluded images (n=416 or 25,4%) could be seen as a limitation. However, the majority of the images were excluded because they did not comply with the prescribed parameter settings. Fourth, our algorithm is not yet capable to distinguish between the different subtypes of non-OA positions, such as right or left occiput transverse and occiput posterior positions. On this basis, the next steps of our ML algorithm will be the implementation of an updated version of the algorithm, which will be able to differentiate among the different subtypes of non-OA positions. Furthermore, our algorithm may seem to have a suboptimal accuracy as compared with the gold standard (around 90%), but it should be taken into account that we employed a training set of about 800 images and, as usual for all ML-based approaches, we expect an improved performance when a larger training set will be available. Finally, another limitation of this work is the lack of repeatability and reproducibility analysis, which will be also specifically addressed in further studies.

CONCLUSION

A newly developed ML-based algorithm for the automatic assessment of the fetal occiput position at TPU can accurately differentiate, in most cases, between OA and non-OA positions. Future studies will specifically address the repeatability and reproducibility of the measurements, as well as the possibility of employing a similar approach to effectively distinguish the different types of non-OA positions.

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Conflict of interest: none to declare

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Figure legend

Figure 1 – Graphical representation of the workflow used to develop the ML-algorithm for the classification between the OA and non-OA fetal head occiput positions.

OA: occiput anterior. ML: machine learning

Figure 2 – Evaluation of the morphological features by the ML-algorithm: a) transperineal scan where the choroid plexus and moulding are visible; b) measurement of the major (A, *brain midline*) and minor (B) axis; c) evaluation of bone interface thickness (C and D); d) position of the center of gravity (M), position of the darkest (*orange*) and lightest (*green*) areas close to the vertical axis.

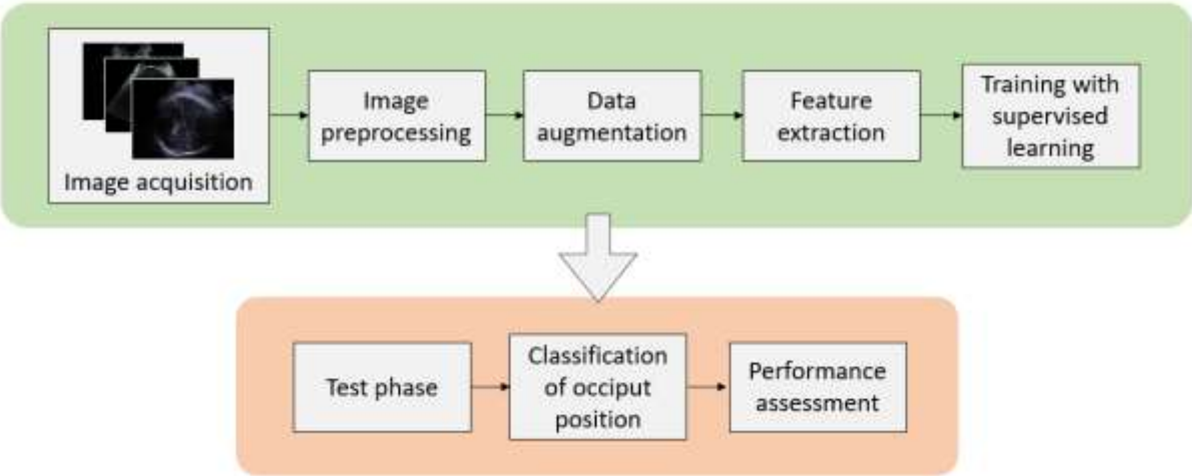
ML: machine learning

Figure 3. Flow diagram of patient enrollment of a non-consecutive series of uncomplicated singleton term pregnancies in the second stage of labor, who got submitted to transperineal ultrasound to obtain an axial view of the fetal head for the training and validation of the Machine Learning (ML) algorithm.

OA: occiput anterior position. ML: Machine Learning.

Table 1 – Participating obstetrical centers and their contribution to the dataset.

Center name	Patients
Parma University Hospital	553
Università Roma Tor Vergata – Ospedale Cristo Re	183
Policlinico Gemelli	138
Kwong Wah Hospital	101
University Hospital of Bari	61
University County Hospital Craiova	50
Kaplan Medical Center	25
Imperial College	25
Mangiagalli Hospital	21
Woman's Clinic Lucerne	13
East Suffolk and North Essex Foundation Trust (ESNEFT)	12
Kwame Nkrumah University	11
Trondheim Hospital	10
Charité Hospital	9
Medias Municipal Hospital	7
Total	1219



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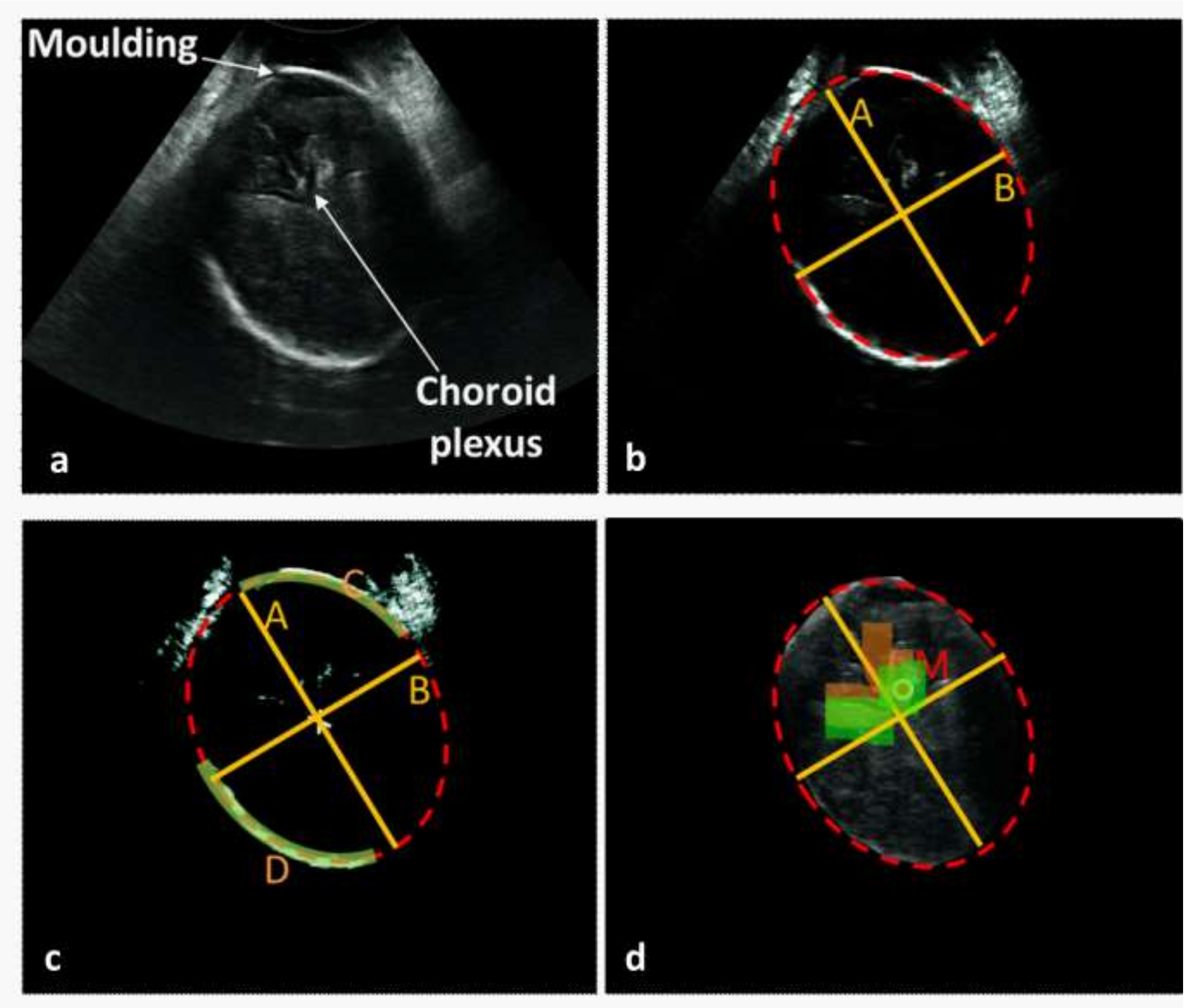

Figure 2 – Evaluation of the morphological features by the ML-algorithm: a) transperineal scan where the choroid plexus and moulding are visible; b) measurement of the major (A, *brain midline*) and minor (B) axis; c) evaluation of bone interface thickness (C and D); d) position of the center of gravity (M), position of the darkest (*orange*) and lightest (*green*) areas close to the vertical axis.

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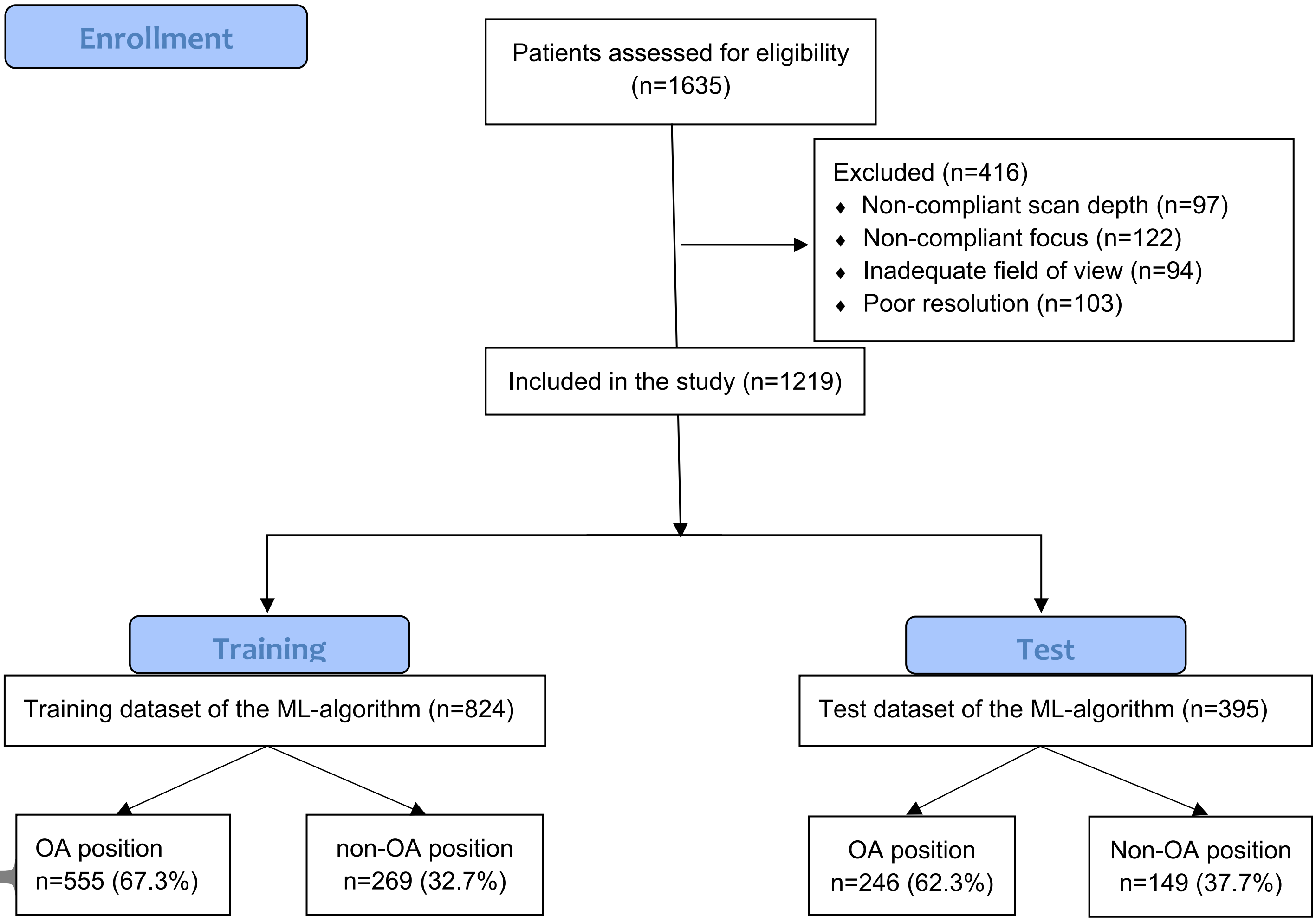

Figure 3. Flow diagram of patient enrollment of a non-consecutive series of uncomplicated singleton term pregnancies in the second stage of labor, who got submitted to transperineal ultrasound to obtain an axial view of the fetal head for the training and validation of the Machine Learning (ML) algorithm.

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