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Full length article

A deep learning approach to identify the fetal head position using transperineal ultrasound during labor

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ABSTRACT

Objectives: To develop a deep learning (DL)-model using convolutional neural networks (CNN) to automatically identify the fetal head position at transperineal ultrasound in the second stage of labor.
Material and methods: Prospective, multicenter study including singleton, term, cephalic pregnancies in the second stage of labor. We assessed the fetal head position using transabdominal ultrasound and subsequently, obtained an image of the fetal head on the axial plane using transperineal ultrasound and labeled it according to the transabdominal ultrasound findings. The ultrasound images were randomly allocated into the three datasets containing a similar proportion of images of each subtype of fetal head position (occiput anterior, posterior, right and left transverse): the training dataset included 70 %, the validation dataset 15 %, and the testing dataset 15 %

Abbreviations: CNN, convolutional neural networks; DL, deep learning; OA, occiput anterior; OP, occiput posterior; OT, occiput transverse.

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of the acquired images. The pre-trained ResNet18 model was employed as a foundational framework for feature extraction and classification. CNN_1 was trained to differentiate between occiput anterior (OA) and non-OA positions, CNN_2 classified fetal head malpositions into occiput posterior (OP) or occiput transverse (OT) position, and CNN_3 classified the remaining images as right or left OT. The DL-model was constructed using three convolutional neural networks (CNN) working simultaneously for the classification of fetal head positions. The performance of the algorithm was evaluated in terms of accuracy, sensitivity, specificity, F1-score and Cohen's kappa.

Results: Between February 2018 and May 2023, 2154 transperineal images were included from eligible participants across 16 collaborating centers. The overall performance of the model for the classification of the fetal head position in the axial plane at transperineal ultrasound was excellent, with an of 94.5 % (95 % CI 92.0—97.0), a sensitivity of 95.6 % (95 % CI 96.8–100.0), a specificity of 91.2 % (95 % CI 87.3–95.1), a F1-score of 0.92 and a Cohen's kappa of 0.90. The best performance was achieved by the CNN_1 – OA position vs fetal head malpositions – with an accuracy of 98.3 % (95 % CI 96.9–99.7), followed by CNN_2 – OP vs OT positions – with an accuracy of 93.9 % (95 % CI 89.6–98.2), and finally, CNN_3 – right vs left OT position – with an accuracy of 91.3 % (95 % CI 83.5–99.1).

Conclusions: We have developed a DL-model capable of assessing fetal head position using transperineal ultrasound during the second stage of labor with an excellent overall accuracy. Future studies should validate our DL model using larger datasets and real-time patients before introducing it into routine clinical practice.

Introduction

Fetal head malposition – defined as any fetal head position that is not occiput anterior (OA) during the second stage of labor [1] – is one of the main determinants of suboptimal instrument placement and incorrect traction direction, leading to failed interventions and adverse neonatal outcomes [2–4]. Therefore, accurately identifying the fetal head position may impact on the safety and success of the assisted vaginal birth [5–7]. Traditionally, the assessment of the fetal head position relies on vaginal digital examination [8]; however, this method has demonstrated low accuracy, ranging from 30 to 70 % regardless of the examiner's experience level [6].

Over the last decade, transabdominal ultrasound has become the gold standard for assessing the fetal head position in labor due to its higher accuracy compared to vaginal digital examination [9–13]. Sonographic assessment of fetal head position has been shown to be feasible also using a transperineal approach [14] which is commonly used to quantify the level of the fetal head in the birth canal. Therefore the main advantage of this approach is that it allows the simultaneous assessment of the fetal head station [15–18] which is to be ascertained prior to considering or performing an operative delivery. However, the diagnosis of fetal position at transperineal ultrasound is challenging for operators with limited experience in fetal brain imaging, as accurate recognition of brain anatomical landmarks is essential for a correct assessment.

Deep learning (DL) algorithms – especially those using convolutional neural networks (CNN) – are considered the leading artificial intelligence tool in medical image analysis [19,20]. A DL algorithm capable of accurately identifying all subtypes of fetal head malposition on transperineally acquired ultrasound images could potentially have a significant impact in clinical settings. To our knowledge, only one prior study has developed and tested an artificial intelligence algorithm – albeit it employed machine learning techniques – to classify an image into OA or non-OA position at transperineal ultrasound with an overall accuracy of 90.6 % [21]. So far, no study has utilized DL for such purpose.

In the present study, we aimed to develop a DL model using CNN to automatically identify the fetal head position and differentiate between specific subtypes of fetal head malpositions – i.e., occiput posterior (OP), right or left occiput transverse (OT) position – at transperineal ultrasound in the second stage of labor.

Materials and methods

This was a prospective multicenter diagnostic study conducted as a part of the "AI OCCIPUT" International Multicenter Clinical Study that started on February 2018. We involved 16 Maternity hospitals worldwide, all affiliated with the International Study group on Labor ANd Delivery Sonography (ISLANDS), with each facility providing transperineal ultrasound images of the fetal head (Table S1). The study was approved by the local ethics committees of each participating unit. An interim analysis of 1219 transperineal axial images of the fetal head was performed to develop a machine learning algorithm. The aim of the study was to evaluated the performance of the algorithm in differentiating between occiput anterior and non-occiput posterior positions [21].

In each collaborating labor ward, we screened for uncomplicated singleton term pregnancies (>37 weeks of gestation) in the second stage of labor, with non-anomalous fetuses in cephalic presentation. We approached the screened women after their admission to the labor ward and obtained written consent prior to enrolment for the anonymized use of the images to train and test the DL algorithm. The images were acquired by obstetricians in charge of the management of each included patient on the basis of a locally validated clinical indication, such as protracted labor, vaginal bleeding, non-reassuring cardiotocography findings, or before performing an operative vaginal delivery. No additional ultrasound scans were conducted outside the standard care provided by the collaborating centers.

Ultrasound assessment

All acquisitions were conducted using either a standard ultrasound machine available in each the labor ward of the collaborating centers. We assessed the fetal head position of all the recruited patients using transabdominal ultrasound, as this is considered to be the gold standard [22,23]. For OP positions, the fetal orbits were oriented upwards; whereas for OT positions, the midline cerebral echo was visible horizontally with the midline fetal brain structures alongside. For OA positions, the probe was rotated 90° to obtain a sagittal plane demonstrating the fetal spine and the occiput anteriorly. We assessed the position of the fetal head in a clockwise manner: left OT positions was defined as occiput ≥2:30 and ≤3:30, right OT positions as ≥8:30 and ≤9:30, OP positions as >3:30 and <8:30, and OA positions as >9:30 and <2:30 [13,24].

Immediately after the transabdominal scan, the attending obstetrician acquired, for each patient, one single image of the fetal head on the axial plane using transperineal ultrasound, as previously reported [14]. Each image was required to demonstrate three intracranial structures as a quality control measurement: 1) the choroid plexus diverging toward the occiput, 2) the fetal skull contour, and 3) the midline echo. The images were labeled as OA, OP, right or left OT based on the transabdominal ultrasound findings and were subsequently uploaded anonymously on a pre-established cloud for remote analysis by the member responsible of each collaborating center. All images were acquired by obstetricians with more than 5 years of experience with intrapartum ultrasound.

Transperineal scan was performed using the following settings: convex probe with 65 mm radius of curvature, field of view 60°, nominal central frequency 3 MHz (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. The acquisition of the images was accomplished as a standard B-Mode image (PNG or BITMAP format with at least 512 × 512 pixels).

Each image underwent independently offline quality assessment by two researchers (M.G.D.T. and F.C.) of the Italian National Research Council, who carefully verified that each image had been acquired according to the prescribed parameter settings (e.g., depth, focus, aperture angle, etc.). If the images did not comply with the prespecified requirements, they were excluded from the study.

We prepared three datasets for the acquired ultrasound images: training dataset, validation dataset and testing data set. The ultrasound images were randomly allocated into the three datasets as follows: the training dataset included 70 %, the validation dataset 15 %, and the testing dataset 15 % of the acquired images. Of note, each dataset contained a similar proportion of images of each fetal head position.

Algorithm architecture and training

The DL model was constructed using three different CNNs, each independently trained, validated and tested for the classification of specific fetal head positions. The pre-trained ResNet18 model was employed as a foundational framework for feature extraction and classification. The first CNN (CNN_1) was trained to differentiate between OA and any type of fetal head malposition. Subsequently, the second CNN (CNN_2) evaluated all fetal head malpositions and classified them into OP or OT position. The third CNN (CNN_3) proceeded with the cases classified as OT and distinguished them between right or left OT (Fig. 1).

Before starting the training phase, a preprocessing and data augmentation phase were executed. In the pre-processing phase, images were normalized and resized to 512 × 512 pixels and the gray level image histogram was optimized to enhance the contrast. 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 geometric transformations (translation and shearing), noise injection (Gaussian and Speckle), and contrast distortion. Therefore, each image in the original dataset underwent five transformations, whose parameters (for example translation distance or the Gaussian filter standard deviation) were randomly chosen, resulting in a training dataset comprising 4120 images (Fig. 2).

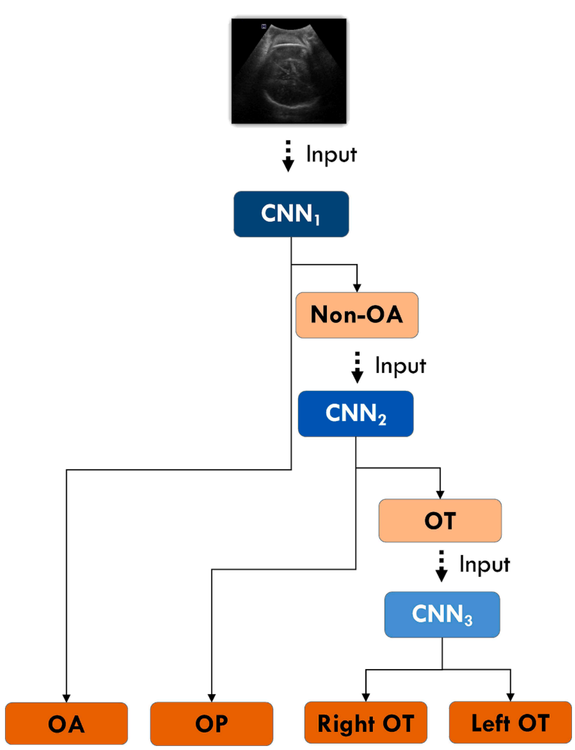

Fig. 1. Flowchart of developed deep learning model using three simultaneous convolutional neural networks (CNN) for the automatic identification of the fetal head position during the second stage labor.

An algorithm was developed to sequentially employ the three CNNs for the ultimate classification process, as follows: 1) CNN_1 was tasked with discerning whether the input image was in an OA or non-OA position. 2) Upon classification of an input image as OA position by CNN_1, the algorithm concludes its processing. 3) If a non-OA position is classified by CNN_1, the subsequent stage engages CNN_2 to classify the input image into OP or OT position. 4) If CNN_2 identifies the image as OP position, the algorithm terminates. 5) If the image is classified as OT position by CNN_2, the final stage involves CNN_3, which classifies the image as in either right or left OT position (Fig. 1).

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

Statistical analysis

The algorithm's performance was evaluated during the testing phase, utilizing the remaining 15 % of the transperineal images, designated as the testing dataset. In the examination of each case, the system remained blinded to the actual occiput position as labeled at transabdominal ultrasound. To evaluate the algorithm's diagnostic performance for the fetal occiput classification into OA, OP, right OT, and left OT positions; the accuracy was calculated as the ratio of correct predictions and the total number of considered images, within each group. The sensitivity was calculated as the ratio between the true positives and the total number of positives (true positives + false negatives), whereas the specificity was the ratio between the true negatives and the total number of negatives (true negatives + false positives). The overall accuracy, sensitivity and specificity were also calculated as described above, by considering OA and non-OA groups together.

Due to the unbalanced numbers of OA and non-OA images, the F1-score was also evaluated as a measure of the algorithm performance [25]. Moreover, the Cohen's kappa was calculated to measure the degree of the agreement between the DL-algorithm and the gold standard (transabdominal ultrasound). The significance level was set at a p-value <0.05.

Between February 2018 and May 2023, 2660 transperineal images of the fetal head in the axial plane were obtained from eligible participants across all 16 collaborating centers worldwide. A total of 506 (19.0 %) images were excluded due to non-compliance with the specified parameter settings (depth, focus) or insufficient contrast. In total, we included 2154 transperineal axial images of the fetal head that were subsequently assigned to one of the three datasets – i.e., training, validation or testing dataset (Fig. 3).

Transperineal images of the fetal head in the axial plane were labeled as OA (n = 1391 or 64.6 %), OP (n = 445 or 20.7 %), right OT (n = 151 or 7.0 %) or left OT (n = 167 or 7.7 %) according to transabdominal ultrasound findings. The training dataset comprised 1503 (69.8 %) images of the overall acquired transperineal images, and included 972/1503 (64.7 %) OA, 310/1503 (20.6 %) OP, 105/1503 (7.0 %) right OT and 116/1503 (7.7 %) left OT positions. The validation dataset comprised 323 (15.0 %) images, and included 207/323 (64.1 %) OA, 69/323 (21.4 %) OP, 22/323 (6.8 %) right OT and 25/323 (7.7 %) left OT positions. Finally, the testing dataset comprised 328 (15.2 %) images, and included 207/328 (63.1 %) OA, 71/328 (22.0 %) OP, 23/328 (7.0 %) right OT and 27/328 (8.2 %) left OT positions.

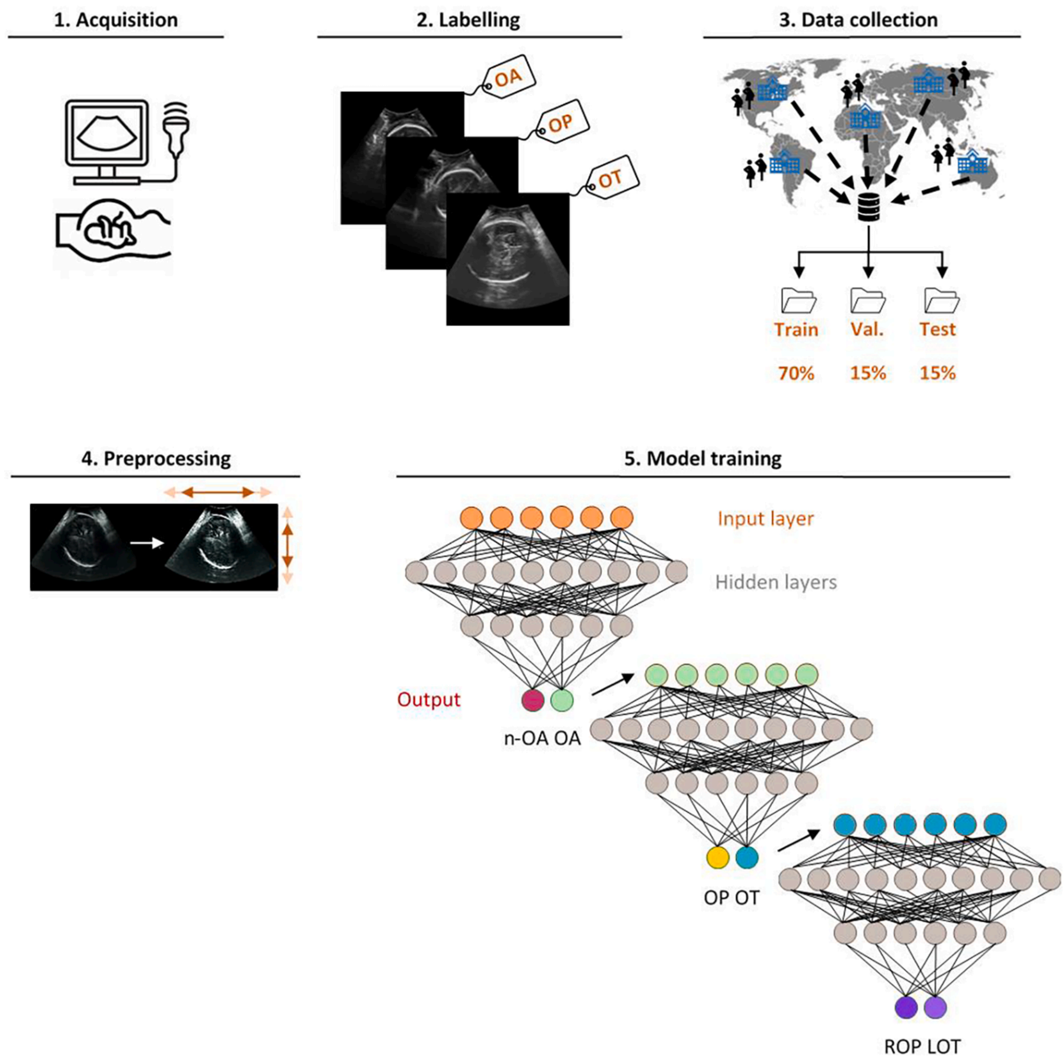

Fig. 2. Workflow outlining the steps performed to develop the deep learning algorithm for the automatic identification of the fetal head position in the second stage of labor. Following data collection, images were classified by an expert gynecologist into occiput anterior (OA), occiput posterior (OP) and right and left occiput transverse (ROT and LOT, respectively), and stored in a database (randomly partitioned into training, validation, and test sets). The images underwent preprocessing (resizing, contrast enhancement, and augmentation) before being fed into the cascade of convolutional neural networks.

The overall accuracy of the DL model on the testing dataset for the classification of the fetal head position in the axial plane at transperineal ultrasound was 94.5 % (95 % CI 92.0–97.0). Moreover, the DL model had a sensitivity of 95.6 % (95 % CI 96.8–100.0), a specificity of 91.2 % (95 % CI 87.3–95.1), and a F1-score of 0.92. The DL model also showed a good agreement with the gold standard with a Cohen's kappa of 0.90 (Table 1).

We also assessed the performance of the algorithm for each subgroup. The best performance was achieved by the CNN_1 which differentiated OA from non-OA positions – i.e., malpositions – with an accuracy of 98.3 % (95 % CI 96.9–99.7), a sensitivity of 98.8 % (95 % CI 96.9–100.0), a specificity of 94.9 % (95 % CI 91.9–97.9). Regarding the differentiation between OP and OT positions, CNN_2 displayed an accuracy of 93.9 % (95 % CI 89.6–98.2), a sensitivity of 96.3 % (95 % CI 90.9–100.0), and a specificity of 90.2 % (95 % CI 84.6–97.8). CNN_3 – i.e., right or left OT position – had the lowest performance among the three CNN with an accuracy of 91.3 % (95 % CI 83.5–99.1), a sensitivity of 91.7 % (95 % CI 81.0–100.0), and a specificity of 88.6 % (95 % CI 75.6–100.0) (Table 1).

The time needed for the DL model to assess the fetal head position of each image was approximately 80 ms.

Discussion

In the present study, we developed a DL model devised to automatically identify fetal head positions on axial transperineal ultrasound images of women in the second stage of labor. The model exhibited strong overall performance in the testing dataset, closely resembling that of the gold standard (transabdominal ultrasound) for distinguishing fetal head malpositions from OA positions. However, its performance declined when identifying specific subtypes of malpositions (CNN_1 accuracy identifying OA vs non-OA position = 98.3 %, CNN_2 accuracy in identifying OP vs OT positions = 93.9 %, CNN_3 accuracy in identifying right OT vs left OT positions = 91.3 %).

The novelty of our study lies in employing DL-based CNNs (i.e., ResNet18) architectures to automatically extract image features (e.g., edges, textures, and shapes) and efficiently learn to identify the fetal head position during labor, thereby enhancing performance compared to other pattern-recognition model, such as traditional machine learning models. So far, only one study has attempted to develop an artificial intelligence-based algorithm for the automatic classification of fetal head position [21]. In this study, the authors employed a machine learning-based algorithm utilizing image processing and filtering, coupled with a pattern-recognition feed-forward neural network to

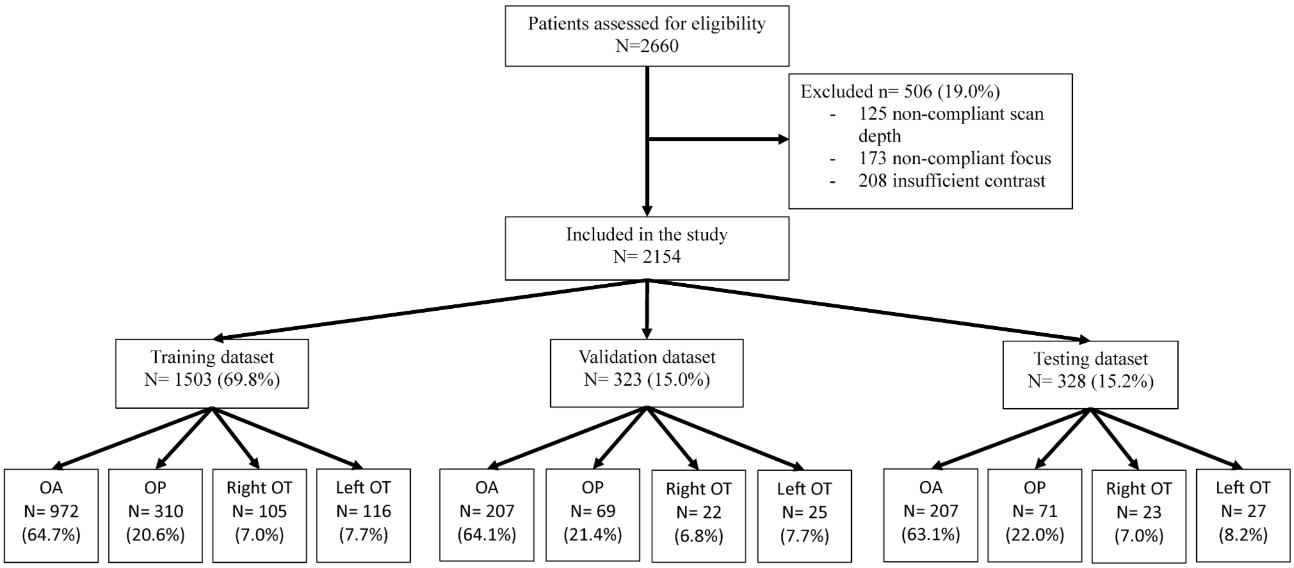

Fig. 3. Study flowchart depicting the enrollment process of uncomplicated singleton term pregnancies in the second stage of labor. These patients were submitted to transperineal ultrasound to obtain an axial view of the fetal head for the development of a deep learning algorithm. The goal was to automatically identify the fetal head position and differentiate between specific subtypes of fetal head malpositions.

Table 1
Performance of the overall deep learning model and each convolutional neural network (CNN) in assessing the fetal head position at axial transperineal ultrasound in the second stage of labor in the testing dataset.

	Accuracy	Sensitivity	Specificity	F1 score	Cohen's k
Overall deep learning model	94.5 % (95 % CI 92.0–97.0)	95.6 % (95 % CI 96.8–100.0)	91.2 % (95 % CI 87.3–95.1)	0.92	0.90
CNN_1 (OA vs non-OA position)	98.3 % (95 % CI 96.9–99.7)	98.8 % (95 % CI 96.9–100.0)	94.9 % (95 % CI 91.9–97.9)	0.97	0.96
CNN_2 (OP vs OT position)	93.9 % (95 % CI 89.6–98.2)	96.3 % (95 % CI 90.9–100.0)	90.2 % (95 % CI 84.6–97.8)	0.92	0.91
CNN_3 (left vs right OT position)	91.3 % (95 % CI 83.5–99.1)	91.7 % (95 % CI 81.0–100.0)	88.6 % (95 % CI 75.6–100.0)	0.86	0.83

OA, occiput anterior. OP, occiput posterior. OT, occiput transverse.

manually extract features of a given image. This algorithm achieved a 90.4 % overall accuracy for the differentiation between occiput anterior positions and fetal head malpositions [21].

When comparing the latter algorithm to CNN_1 – both designed for the same purpose, namely the differentiation between OA and malpositions – CNN_1 demonstrates a higher performance, achieving over 98 % accuracy in identifying fetal head malpositions. This represents an approximately 8 % increase in the accuracy compared to the machine learning-based algorithm. Our results highlight the advantages of using a DL-based approach for image classification in terms of accuracy and efficiency compared to other artificial intelligence-based approaches. Additionally, we observed a significant improvement in execution time, with the CNN-based approach reducing the processing time from 390 ms with the machine learning-based algorithm to 80 ms for the classification of the fetal head position during labor.

The performance of CNN_2 and CNN_3 was lower than that of CNN_1, which was expected due to the lower number of available images for OP and OT positions. This difference resulted from the lower prevalence of OP and OT positions in labor [26]; thus, making the training dataset for CNN_2 and CNN_3 smaller. Although CNN_2 achieved a very good accuracy of nearly 94 % and CNN_3 a good accuracy of 91 %, they underperformed when compared to CNN_1. This led to an overall reduction in the DL model's performance. We hypothesized that augmenting the training datasets for both CNNs might enhance the model's ability to generalize and improve their accuracy, which is commonly seen in DL-based algorithms [19,20]. Nevertheless, the scarcity of data on DL models for the assessment of the fetal head position prevents us from making direct comparisons with other datasets.

Fetal head malposition represents a significant risk factor associated with suboptimal instrument placement and incorrect traction direction, thereby increasing the risk of failed assisted vaginal birth and adverse neonatal outcomes [2–4]. As such, transabdominal ultrasound has been proposed to accurately identify the position of the fetal occiput prior to performing an operative vaginal delivery, thereby potentially increasing the safety and the success of the extraction maneuver [27,28]. Recently, transperineal ultrasound has gained popularity for the assessment of fetal head position in labor, as it does not only demonstrate a similar accuracy to transabdominal ultrasound [14], but also allows the simultaneous assessment of the fetal head station and rotation [15–18]. However, the assessment of the fetal head position at transperineal approach is challenging for operators with little experience in fetal brain imaging, as accurate recognition of brain anatomical landmarks is essential for a correct assessment [14].

The main clinical utility of our DL model lies in its fully automated capability to accurately differentiate among all subtypes of fetal head malpositions. This may provide obstetricians, especially those with less experience, with a reliable and fast recognition tool for the fetal head position. Additionally, our DL model could be integrated with other DL models capable of automatically assessing the fetal head station [29,30], providing a complete assessment of the fetal head position and station during labor. This approach has the potential to be objective and time-saving [31–34], particularly in situations where quick clinical decisions, such as instrumental vaginal delivery due to suspected intrapartum fetal compromise, are needed.

The main strength of our study lies in the robustness of our DL model, which was trained, validated and tested using a large dataset consisting of transperineal images obtained from 16 different hospitals worldwide. Additionally, the data were collected prospectively and provided by experienced sonographers specialized in the field of intrapartum ultrasound.

There are also some limitations that must be acknowledged. First, the dataset contained a limited number of images depicting fetal head malpositions (i.e., OP and OT), potentially impacting the accuracy of the DL model, especially for specific subtypes of malpositions. Guaranteeing a balanced dataset with high-quality data is crucial as it significantly contributes to improving the accuracy and generalization of the model, ensuring equitable representation across different classes. However, we expect an improved performance of the DL-algorithm with the incorporation of a more representative dataset. Second, the analysis of the transperineal images by the DL model was conducted offline, precluding us from drawing conclusions regarding the performance of the DL model in a real-world scenario with live patients. This aspect will be the focus of future studies. Third, we trained our DL model using a supervised approach, where human operators manually selected and labeled the images. This introduces the possibility of inherent selection bias in the images included for training and testing the DL model.

In conclusion, we have developed the first DL model capable of accurately assessing fetal head position using transperineal ultrasound during the second stage labor. More importantly, our DL model can differentiate between specific subtypes of fetal head malpositions, which makes it a potential clinical tool in the management of fetal malpositions in the labor ward. Future studies should validate our DL model using larger datasets and live patients before introducing it into routine clinical practice.

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CRediT authorship contribution statement

Ruben Ramirez Zegarra: Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **Francesco Conversano:** Writing – original draft, Software, Formal analysis, Data curation, Conceptualization. **Andrea Dall'Asta:** Writing – review & editing, Formal analysis, Data curation, Conceptualization. **Maria Giovanna Di Trani:** Writing – original draft, Software, Methodology, Formal analysis, Data curation. **Stefania Fieni:** Writing – review & editing, Data curation. **Rocco Morello:** Software, Formal analysis, Data curation. **Chiara Melito:** Writing – review & editing, Data curation. **Paola Pisani:** Software, Formal analysis, Data curation. **Enrico Iurlaro:** Writing – review & editing, Data curation. **Marta Tondo:** Writing – review & editing, Data curation. **Dominic Gabriel Iliescu:** Writing – review & editing, Data curation. **Rodica Nagy:** Writing – review & editing, Data curation. **Edvin Vaso:** Writing – review & editing, Data curation. **Michael Abou-Dakn:** Writing – review & editing, Data curation. **Gülhan Muslu:** Writing – review & editing, Data curation. **Wailam Lau:** Writing – review & editing, Data curation. **Catherine Hung:** Writing – review & editing, Data curation. **Angelo Sirico:** Writing – review & editing, Data curation. **Antonio Lanzone:** Writing – review & editing, Data curation. **Giuseppe Rizzo:** Writing – review & editing, Data curation. **Ilenia Mappa:** Writing – review & editing, Data curation. **Christoph Lees:** Writing – review & editing, Data curation. **Sana Usman:** Writing – review & editing, Data curation. **Alice Winkler:** Writing – review & editing, Data curation. **Christian Braun:** Writing – review & editing, Data curation. **Roni Levy:** Writing – review & editing, Data curation. **Edi Vaisbuch:** Writing – review & editing, Data curation. **Wassim A. Hassan:** Writing – review & editing, Data curation. **Sasha Taylor:** Writing – review & editing, Data curation. **Antonella Vimercati:** Writing – review & editing, Data curation. **Allegra Mazzeo:** Writing – review & editing, Data curation. **Torbjørn Moe Eggebø:** Writing – review & editing, Data curation. **Yaw Amo Wiafe:** Writing – review & editing, Data curation. **Tullio Ghi:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Conceptualization. **Sergio Casciaro:** Writing – review & editing, Supervision, Software, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ejogrb.2024.08.012.

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