Original Article

Combining pelvic floor ultrasonography with deep learning to diagnose anterior compartment organ prolapse

Fan Yang[1,2#], Rong Hu[1#], Hongjie Wu[3], Shichang Li[3], Shiyun Peng[1], Hong Luo[1*], Jiancheng Lv[3*], Yueyue Chen[4], Ling Mei[4]

[1]Department of Ultrasonography, West China Second University Hospital, Sichuan University and Key Laboratory of Birth Defects and Related Diseases of Women and Children (Sichuan University), Ministry of Education, Chengdu, China; [2]Chengdu Chenghua District Maternal and Child Health Hospital, Chengdu, China; [3]College of Computer Science, Sichuan University, Chengdu, China; [4]Department of Obstetrics and Gynecology, West China Second University Hospital, Sichuan University and Key Laboratory of Birth Defects and Related Diseases of Women and Children (Sichuan University), Ministry of Education, Chengdu, China

Contributions: (I) Conception and design: F Yang, H Luo, J Lv; (II) Administrative support: H Luo, J Lv; (III) Provision of study materials or patients: Y Chen, L Mei; (IV) Collection and assembly of data: R Hu, H Wu, S Li, S Peng; (V) Data analysis and interpretation: F Yang, H Wu, H Luo, J Lv; (VI) Manuscript writing: All authors; (VII) Final approval of manuscript: All authors.

[#]These authors contributed equally to this work as co-first authors.

*These authors contributed equally to this work.

Correspondence to: Prof. Hong Luo, MD, PhD. Department of Ultrasonography, West China Second University Hospital, Sichuan University and Key Laboratory of Birth Defects and Related Diseases of Women and Children (Sichuan University), Ministry of Education, 20, Section 3, Renmin South Road, Chengdu 610041, China. Email: luohongcd1969@163.com; Prof. Jiancheng Lv, PhD. College of Computer Science, Sichuan University, 24, South Section 1, First Ring Road, Chengdu 610065, China. Email: lvjiancheng@scu.edu.cn.

Background: Anterior compartment prolapse is a common pelvic organ prolapse (POP), which occurs frequently among middle-aged and elderly women and can cause urinary incontinence, perineal pain and swelling, and seriously affect their physical and mental health. At present, pelvic floor ultrasound is the primary examination method, but it is not carried out by many primary medical institutions due to the significant shortcomings of training in the early stage and the variable image quality. There has been great progress in the application of deep learning (DL) in image-based diagnosis in various clinical contexts. The main purpose of this study was to improve the speed and reliability of pelvic floor ultrasound diagnosis of POP by training neural networks to interpret ultrasound images, thereby facilitating the diagnosis and treatment of POP in primary care.

Methods: This retrospective study analyzed medical records of women with anterior compartment organ prolapse (n=1,605, mean age 45.1±12.2 years) or without (n=200, mean age 38.1±13.4 years), who were examined at West China Second University Hospital between March 2019 and September 2021. Static ultrasound images of the anterior chamber of the pelvic floor (5,281 abnormal, 535 normal) were captured at rest and at maximal Valsalva motion, and four convolutional neural network (CNN) models, AlexNet, VGG-16, ResNet-18, and ResNet-50, were trained on 80% of the images, then internally validated on the other 20%. Each model was trained in two ways: through a random initialization parameter training method and through a transfer learning method based on ImageNet pre-training. The diagnostic performance of each network was evaluated according to accuracy, precision, recall and F1-score, and the receiver operating characteristic (ROC) curve of each network in the training set and validation set was drawn and the area under the curve (AUC) was obtained.

Results: All four models, regardless of training method, achieved recognition accuracy of >91%, whereas transfer learning led to more stable and effective feature extraction. Specifically, ResNet-18 and ResNet-50

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performed better than AlexNet and VGG-16. However, the four networks learned by transfer all showed fairly high AUCs, with the ResNet-18 network performing the best: it read images in 13.4 msec and provided recognition an accuracy of 93.53% along with an AUC of 0.852.

Conclusions: Combining DL with pelvic floor ultrasonography can substantially accelerate diagnosis of anterior compartment organ prolapse in women while improving accuracy.

Keywords: Ultrasonography; deep learning (DL); neural network; organ prolapse; female pelvic floor

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Introduction

Pelvic organ prolapse (POP), which affects many women in middle age and older (1,2), occurs when one or more pelvic organs protrude out of the vagina via the vaginal fascia, leading to problems such as cystocele, uterine prolapse, and rectocele (3), as well as urinary incontinence, fecal incontinence, perineal pain and swelling, which seriously reduce physical and mental health (4). The anterior compartment is the most common site of prolapse. Anterior compartment prolapse refers to prolapse of the anterior vaginal wall and is inclusive of urethrocele and cystocele (5). Due to the growth in China's ageing population, the proportion of POP is predicted to increase (6). A substantial proportion (38–76%) of women who experience prolapse require hospitalization, of whom 10–20% require surgery (7). Unfortunately, without adequate recognition and treatment of the multilocular component of the disease process, surgery may not be curative, and the rate of repeat surgery is as high as 30% (8). It is becoming increasingly clear that clinical assessment alone is insufficient to assess pelvic floor function and anatomy, as it describes superficial anatomy rather than true structural abnormalities. Compounding matters, clinical assessment is often influenced by unrecognized confounding factors such as bladder filling and Valsalva motion duration, which can cause the intraoperative findings to be inconsistent with the outpatient diagnosis (9). The ability of the physical examination to accurately detect the underlying pathophysiology varies greatly, and surgeons are beginning to increasingly rely on imaging. Pelvic floor ultrasonography is currently widely used for POP (10-12), which can visualize the anatomical position of pelvic organs and their support systems in real time at relatively low cost and without the need for radiation. Meanwhile, it can also detect minor prolapse that cannot be detected clinically.

Correctly interpreting the ultrasound images requires extensive training and imaging quality can be variable. These disadvantages likely contribute to the fact that many primary medical institutions do not perform pelvic floor ultrasonography. Given the advances in applying deep learning (DL) to image-based diagnosis in various clinical contexts, including ultrasonography (13,14), we wondered whether we could improve the speed and reliability of pelvic floor ultrasonography for diagnosing POP by training neural networks to interpret the ultrasound images, and more hopefully to provide assistance in pelvic floor prolapse screening and diagnosis to primary hospitals. Therefore, we aimed to further promote the popularization of pelvic floor ultrasound, so as to benefit more grassroots people.

In recent years, AlexNet (15), VGGNet (16), and ResNet (17) have been widely used as pre-trained convolutional neural networks (CNNs) that learn from a large number of general images. However, without further training, these CNNs may not correctly identify medical images. Therefore, this study was performed to develop models for the diagnosis of anterior POP based on these CNNs, and evaluate the diagnostic efficacy of the models. We drew our data from the medical records of patients at West China Second University Hospital who were screened for anterior compartment organ prolapse, which involves the urethra, bladder, or anterior vaginal wall. We present this article in accordance with the TRIPOD+AI reporting checklist (available at https://qims.amegroups.com/article/view/10.21037/qims-24-772/rc).

Methods

The study was conducted in accordance with the Declaration of Helsinki (as revised in 2013). This retrospective study was approved by the Medical Ethics Committee of West China Second University Hospital (No.

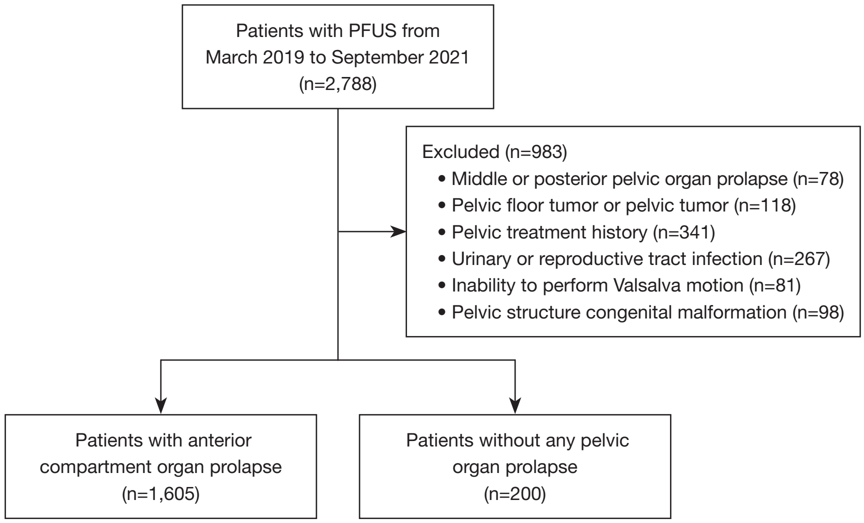

Figure 1 Flowchart of patient enrollment. PFUS, pelvic floor ultrasonography; POP, pelvic organ prolapse.

2023.317), and the requirement for individual consent for this retrospective analysis was waived.

Patients

We retrospectively analyzed medical records for a consecutive series of women who underwent pelvic floor ultrasonography at West China Second University Hospital between March 2019 and September 2021 (n=2,788). To be included in the study, patients had to have complete data available for their gynecological history, conventional ultrasound images, and the ability to perform the Valsalva motion correctly. Patients were excluded if they had middle pelvic or posterior POP (n=78), pelvic floor tumors or pelvic tumors (n=118), history of pelvic surgery or treatment for acute or chronic pelvic inflammatory disease (n=341), infection of the lower urinary tract or reproductive tract in the acute stage (n=267), or congenital malformation of the pelvic floor or any pelvic structures (n=98). Patients were also excluded if they could not perform the Valsalva procedure correctly due to severe prolapse symptoms (n=81). Among them, patients with anterior compartment organ prolapse based on signs and symptoms in accordance with the "pelvic organ prolapse quantitation" method (18) constituted the abnormal group, and those without any POP were allocated to the normal group (*Figure 1*). According to the above criteria, 59 cases in the abnormal group and 12 cases in the normal group from June to August 2024 in West China Second University Hospital were collected as the new external validation set.

Pelvic floor ultrasonography and dataset of ultrasound images

Two-dimensional static images of the anterior compartment of the pelvic floor while the patient was at rest and under maximal Valsalva motion were obtained from all participants by three physicians who performed pelvic floor ultrasonography in our institution using a color Doppler ultrasound system (Resona OB, Mindray, Shenzhen, China) equipped with a DE10-3U volume probe at a frequency of 4–8 MHz. The maximum Valsalva state was defined as the action of increasing abdominal pressure by holding breath downward after deep inspiration, the movement of pelvic organs to dorsocaudal side or the enlargement of levator hiatus, which lasted ≥6 seconds. During pelvic floor ultrasound examination, the probe was placed in the middle of the perineum of the patient, the indicator point was toward the ventral side of the patient, and the direction of the sound beam was parallel to the sagittal plane of the human body to obtain the standard median sagittal section of the pelvic floor. This section showed the posterior inferior margin of the pubic symphysis, urethra, bladder, vagina, ampulla of rectum, anal canal, and levator ani muscle (*Figure 2*).

All pictures that showed the standard median sagittal section of the pelvic floor and clearly showed the structure of the pelvic floor were included in the study. Finally, for

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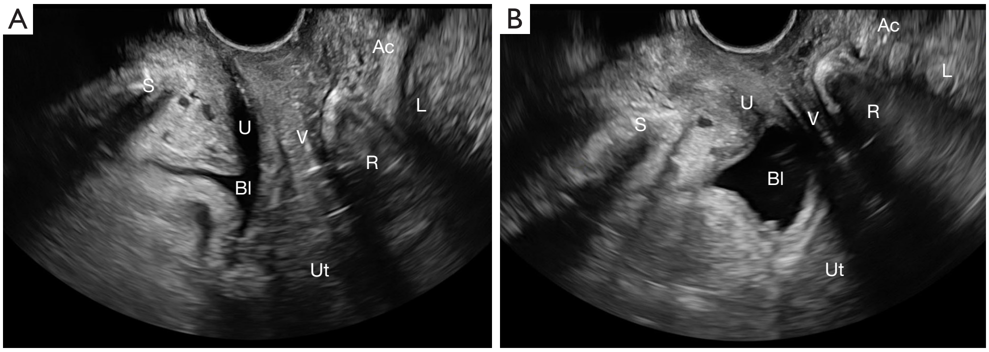

Figure 2 Median sagittal section of the pelvic floor. (A) Resting state; (B) maximal Valsalva maneuver state. S, symphysis pubis; U, urethra; Bl, Bladder; V, vagina; Ut, uterus; Ac, Anal canal; R, rectum; L, levator ani muscle.

training neural networks to interpret pelvic floor ultrasound images, we drew on a final dataset of 5,281 abnormal midsagittal images (with 3,423 in the maximal Valsalva motion) and 535 normal midsagittal images (with 360 in the maximal Valsalva motion). We randomly defined 4,652 images (80% of the dataset) as the training set and 1,164 (20% of the dataset) as the test set.

CNNs to interpret pelvic floor ultrasound images

The network parameters needed to be initialized before training. In order to minimize the error between the predicted value and the actual labels, a loss function was defined to measure the difference between the two values. Then, the back propagation algorithm and various optimization algorithms were used to optimize the parameters of the neural network and find the appropriate network parameters, so that the training process of the neural network was faster and more stable.

We trained four CNNs: AlexNet, VGG-16, ResNet-18, and ResNet-50 through a Pytorch DL framework (https://pytorch.org/) using Ubuntu 18.04 (https://ubuntu.com/) running on an Intel Xeon E5-2620 v4 (https://www.intel.com/) and dual-channel Titan Xp GPU (NVIDIA, Santa Clara, CA, USA). For training, image pixel size was adjusted to 224×224, and the following four data enhancement operations were performed to expand the range of training images: random horizontal flip, random rotation, color jitter, and normalization (Figure S1). During internal validation on the test set, images were enhanced only through normalization. During training, the batch size was 32, Adam optimizer (19) was used, epoch count was 100, and the learning rate was initially 0.01, after which it decreased by 20% every 20 epochs.

This study divides the training of each neural network into two ways: random initialization and transfer learning (parameter initialization by loading the pre-trained model) (20), in order to compare the training efficiency of the two methods.

Transfer learning is a technique that uses pre-trained models to suit a new dataset, which can enable neural network models to better learn the generalization features of images, effectively accelerate the training speed, and improve the accuracy (21,22). In this study, transfer learning drew on the ImageNet database [ImageNet (image-net.org)] containing more than 15 million images spanning 20,000 categories. The four neural networks were pre-trained on the ImageNet database, then fine-tuned on pelvic floor ultrasound images (Figure S2).

Evaluation of the CNNs

The identification results were true positive (TP), false positive (FP), true negative (TN), and false negative (FN). The diagnostic performance of each network was assessed in terms of accuracy, precision, recall, and F1-score as described (23,24). These measures were calculated as follows:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad [1]$$

$$Precision = \frac{TP}{TP + FP} \quad [2]$$

$$Recall = \frac{TP}{TP + FN} (= Sensitivity) \quad [3]$$

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Table 1 Patient characteristics

Variables	Abnormal group	Normal group	P value	Training set	Test set	P value
n	1,605	200	–	4,652	1,164	–
Age (years), mean ± SD	45.1±12.2	38.1±13.4	<0.01	40.0±13.1	41.0±14.7	0.08

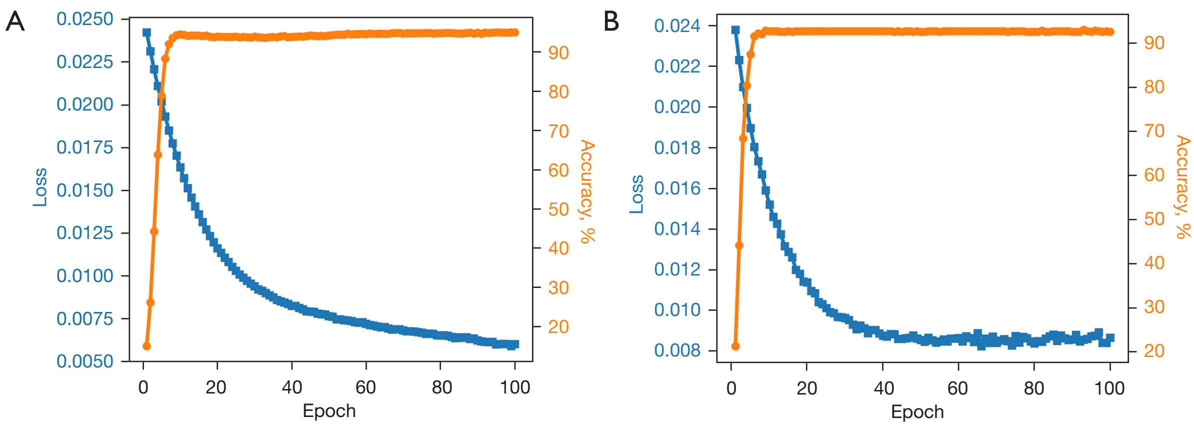

Figure 3 Loss function and accuracy of the ResNet-18 model against the (A) training set and (B) test set of pelvic floor ultrasound images. The model was trained on transfer learning model.

$$F1\text{-}score = \frac{2}{\frac{1}{Precision} + \frac{1}{Recall}} \quad [4]$$

Then the receiver operating characteristic (ROC) curves of each network in the training and validation sets were plotted separately. The ROC curve is a graphical image showing the diagnostic ability of a binary classifier when its discrimination threshold changes (25), and the area under the ROC curve (AUC) is a standard indicator in model evaluation.

In addition, the rationality of image classification by neural networks was also assessed using gradient-weighted class activation mapping (26,27). Class activation mapping provides visualization of the most important activation mapping for the target class. It provides a sign that indicates what is the focus of the network.

Comparator sonographers

A group of three sonographers who worked at the ultrasound department of West China Second University Hospital, with more than five years of pelvic ultrasound experience were defined as the comparable group. They were enlisted to evaluate the performance of the training set images, and the average evaluation time of each case was recorded. The evaluation results were summarized, and when there was a discrepancy, a more senior sonographer would evaluate and draw a final conclusion, and then the accuracy of manual evaluation was calculated.

Results

We obtained a dataset of 5,816 pelvic floor ultrasound images from the abnormal group of 1,605 women with anterior compartment organ prolapse (mean age 45.1±12.2 years) and the normal group of 200 women without POP (mean age 38.1±13.4 years), of which 4,652 (average age 40.0±13.1 years) were allocated to the training set and 1,164 (average age 41.0±14.7 years) were allocated to the test set (*Figure 1*, *Table 1*).

Both in the training set and test set, the ResNet-18 network reached maximum accuracy of 92–93% within 20 iterations, and the loss function, which measures the error between the network output and the actual data, decreased to a certain extent and tended to be stable (*Figure 3*). Similar results were obtained for the other three networks. These results illustrate that the network learned deep features of ultrasound images from women with or without anterior compartment organ prolapse and was able

Table 2 Diagnostic performance of the four convolutional neural networks against the test set of pelvic floor ultrasound images

Operator or network	Training method	Precision (%)	Recall (%)	F1-score (%)	Accuracy (%)	Time per image (msec)
Human	–	–	–	–	89.51	15,700
AlexNet	RI	92.72	98.54	95.54	91.68	10.7
	TL	93.13	98.98	95.97	92.47	10.7
VGG-16	RI	92.29	99.56	95.79	92.07	25.4
	TL	93.99	98.25	96.07	92.73	25.4
ResNet-18	RI	93.05	99.71	96.26	93.00	13.4
	TL	94.92	98.10	96.48	93.53	13.4
ResNet-50	RI	93.86	98.25	96.01	92.60	21.3
	TL	94.28	98.69	96.43	93.39	21.3

RI, random initialization; TL, transfer learning.

Table 3 Diagnostic performance of the four convolutional neural networks against the new validation set of pelvic floor ultrasound images

Operator or network	Training method	Precision (%)	Recall (%)	F1-score (%)	Accuracy (%)	Time per image (msec)
Human	–	–	–	–	87.53	18,700
AlexNet	RI	89.33	95.78	92.44	87.06	10.7
	TL	87.30	99.40	92.96	87.56	10.7
VGG-16	RI	90.96	96.99	93.88	89.55	25.4
	TL	91.01	97.59	94.19	90.05	25.4
ResNet-18	RI	93.06	96.99	94.99	91.54	13.4
	TL	94.15	96.99	95.55	92.54	13.4
ResNet-50	RI	93.14	98.19	95.60	92.54	21.3
	TL	95.24	96.39	95.81	93.03	21.3

RI, random initialization; TL, transfer learning.

to differentiate them accurately.

The results of comparison of the four networks, each trained in two ways, showed that the diagnostic speed of AlexNet, VGG-16, ResNet-18, and ResNet-50 for each image was 10.7, 25.4, 13.4, and 21.3 msec, respectively, whereas the average diagnostic speed of human was 15,700 msec. The diagnostic accuracy of these four networks was above 90% (89.51% for human). That is to say, all four greatly accelerated diagnosis of anterior compartment organ prolapse with better accuracy than a human (*Table 2*). The precision, recall, F1-score, and accuracy all showed that transfer learning led to better performance than random initialization in all four networks. Even without transfer learning, ResNet-18 and ResNet-50 performed better than AlexNet and VGG-16, presumably because they contain a residual connection module, which helps the network fully extract pelvic floor features and accelerates convergence (28). As a result, both of them have excellent performance in anomaly detection on training set, test set, and even external data verification (*Table 3*).

In both the training sets, all four networks that through transfer learning showed quite high AUCs, all greater than 0.95. In the test set, ResNet-18 and ResNet-50 had larger AUCs than AlexNet and VGG-16, with 0.852 and 0.822, respectively (*Figure 4*).

The rationality of image classification was confirmed for ResNet-18 by class activation mapping, which showed that the network paid more attention to clinically relevant

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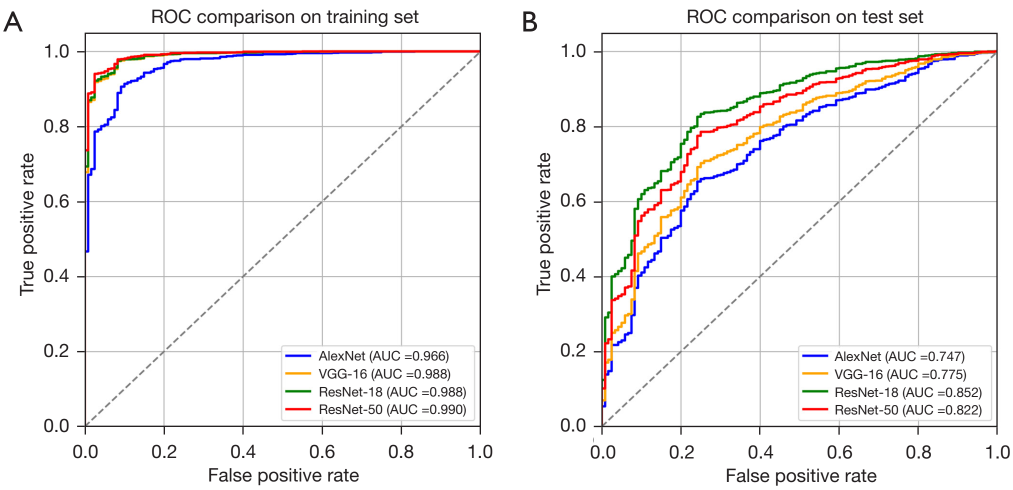

Figure 4 Comparison of the diagnostic performance of the four CNNs, in terms of AUCs, against the (A) training set or (B) test set of pelvic floor ultrasound images. Networks were trained on transfer learning model. CNNs, convolutional neural networks; ROC, receiver operating characteristic; AUCs, areas under ROC curves.

regions of ultrasound images (*Figure 5*).

Discussion

Anterior compartment organ prolapse, including anterior vaginal prolapse, urethrocele, and cystocele, is the most common POP and has deleterious effects on women's health (29). Although clinical examination can be used to evaluate the disease, this remains a relatively subjective measure; it can be affected not only by the skill of the examiner, but also by the ability of the patient to perform the maximum Valsalva motion. Ultrasound is a simple, inexpensive, and harmless diagnostic modality that is easy to implement and is the first choice for most gynecological examinations. Studies have shown that ultrasound has a good diagnostic value in POP (30,31).

DL is a method that extracts hierarchical features from the original input image through its self-learning ability, and finally forms high-level abstract features through iteration, so as to perform classification, which has gained popularity due to its recent success in image segmentation and classification applications (32). In this study, DL and pelvic floor ultrasound were combined to automatically identify and diagnose anterior compartment organ prolapse. The results showed that the current generation of CNNs can rapidly and reliably diagnose anterior compartment organ prolapse, and that transfer learning can improve their diagnostic performance. In fact, the networks provided thousand-fold faster diagnosis with better accuracy than an experienced clinician. There have been reports of DL in magnetic resonance imaging diagnosis of POP (33), but this is the first application of DL to ultrasound diagnosis of anterior compartment organ prolapse.

Our work extends the contexts in which neural networks have been shown to be highly capable at image classification (34,35). Our comparisons suggest that transfer learning can improve diagnostic performance. Neural networks require training on extremely large amounts of data in order to perform accurately without overfitting. Medical image datasets such as the one in the present study are relatively small, so we used data augmentation and transfer learning to help the networks learn to generalize features to a broad range of situations.

This study justifies further exploration of how to apply DL to anterior compartment organ prolapse. However, further research and improvement are still needed. First, this study was a single-center study with a relatively single source of data, and subsequently our findings should be verified and extended in larger, preferably multi-site studies. Second, the models should also be tested for their ability to diagnose situations that are not binary (yes/no) but more nuanced, such as differentiating less and more severe prolapse. Finally, although the models in this study have high accuracy, future work should also train models with datasets that include pelvic ultrasound images from more diverse data for practical clinical use.

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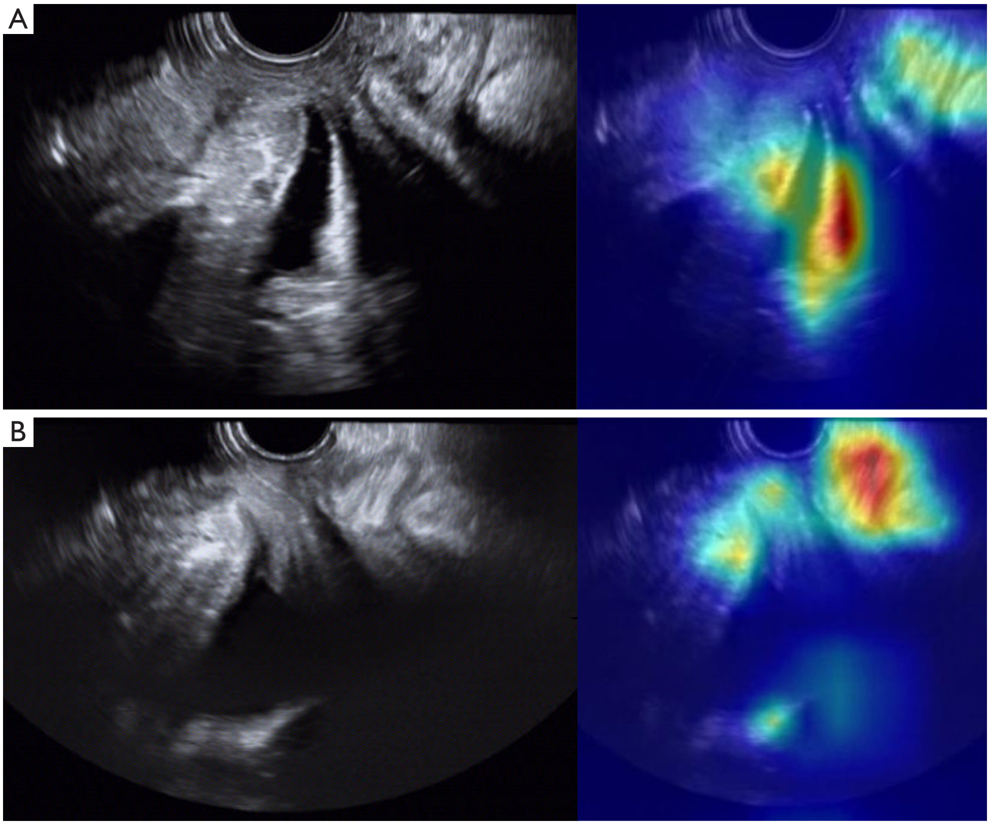

Figure 5 Examples of class activation mapping to assess where the ResNet-18 network, trained on transfer learning model, paid greater attention during classification of pelvic floor ultrasound images in the training set. (A) Organ prolapse; (B) normal control. Red indicates more attention; blue, less attention.

Conclusions

Our study suggests that DL enables CNNs to diagnose anterior compartment organ prolapse in women much faster and slightly better than humans. This work may help promote the use of pelvic floor ultrasonography for diagnosing this condition and facilitate the development of pelvic floor ultrasound in primary care. It may also catalyze the application of DL to other types of ultrasound image classification.

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Footnote

Reporting Checklist: The authors have completed the TRIPOD+AI reporting checklist. Available at https://qims.amegroups.com/article/view/10.21037/qims-24-772/rc

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Ethical Statement: The authors are accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved. The study was conducted in accordance with the Declaration of Helsinki (as revised in 2013). The study was approved by the Medical Ethics Committee of West China Second University Hospital (No. 2023.317) and the requirement for individual consent for this retrospective analysis was waived.

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