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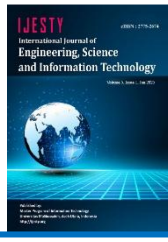

A Deep Learning-Based Pipeline for Feature Extraction and Segmentation of Endometriosis Stages: A Comparative Study of Transfer Learning and CDGAN Models

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Abstract

Top of Form This study proposes a deep learning-driven approach for extracting features and segmenting various stages of endometriosis from ultrasound images. The proposed pipeline integrates transfer learning with pretrained convolutional neural networks (CNNs) and conditional generative adversarial networks (CDGANs) to improve the accuracy and interpretability of the segmentation process. ResNet and DenseNet models are used in transfer learning to fine-tune pre-trained networks that classify the stages of endometriosis, and the performance of the model is improved by applying CDGAN on the dataset through data augmentation. From the comparison, the CDGAN-based method is more accurate and easier to interpret than the transfer learning model, so it is the preferred method for automatic staging of endometriosis. The results show improved accuracy (90%) and a higher F1-score (0.88), with CDGAN delivering the best segmentation results even in the most complex examples. Automating this portion of medical imaging for endometriosis has the potential to result in more informed treatment choices.

Keywords: *Deep Learning, Endometriosis, Feature Extraction, Segmentation, Transfer Learning.*

1. Introduction

In endometriosis, similar cells to those in the uterine lining grow in other areas, leading to pain, infertility and a range of health issues. Diagnosis, personal treatment plans and a patient's well-being all depend on correctly classifying the stages of Endometriosis. Early and reliable staging lets doctors figure out if the disease is serious and decide on the right treatment which may stop the condition from advancing and lower the risks for infertility. Still, usual methods of diagnosis require surgical procedures such as laparoscopy, that often take time, are expensive and may be difficult for patients. So, the use of medical imaging is extremely important for diagnosing and categorizing Endometriosis without invasive procedures.
Ultrasound, as a key medical imaging technique, is crucial in detecting Endometriosis by revealing the disease's location and severity. However, manual analysis of these images is prone to human error and can be subjective. Deep learning is assisting medical image analysis, especially with the CNN family, to help make disease diagnosis fast and accurate.
Modern improvements have not yet made it possible to clearly distinguish various stages of Endometriosis only with deep learning from ultrasound images. Most existing studies concentrate on simple ways to form classes and mixing modern techniques like Transfer Learning and CDGANs for enhanced performance in classification and segmentation has not been explored much.
The paper outlines a complete deep learning process where feature extraction, segmentation and classification are combined to look for Endometriosis stages automatically. This study uses Transfer Learning and CDGAN to try to make the classification process more accurate and clearer. To be precise, the research work is planned with these objectives:
1. To propose a pipeline with feature extraction, segmentation, and deep learning architectures for Endometriosis stage classification.
2. To apply transfer learning for classification with higher accuracy.
3. To apply CDGAN with XAI (Explainable AI) for classification with improved accuracy and interpretability.

The most important contributions are: building a new deep learning framework with multiple models for staging Endometriosis and comparing Transfer Learning and CDGAN approaches. The new method aims to better the accuracy of staging classes and stresses increasing interpretability, an important factor for making informed clinical choices.
The following sections discuss: existing research on ranking Endometriosis and how deep learning techniques are relevant. In Section III, the nature of the pipeline architecture and the models applied to feature creation, segmenting and classifying are both explained. In Section IV, information on the experimental setup, data used and evaluation methods is provided to see how the models perform. Section V studies the outcomes and measures how well Transfer Learning and CDGAN do at categorizing the stages of Endometriosis. The ends of the paper are covered in Section VI, where the findings are announced and future directions for research are suggested.

2. Literature Review

In their study, Zhang and Qing [1] introduce a way to extract and segment features in medical images using a deep learning approach. They train a stacked denoising autoencoder (SDA) to extract useful features from unlabelled image blocks. After that, they fine-tune these features further by using labelled samples so that the model can recognize image categories. For this purpose, threshold segmentation and morphological methods are used on the brain tumour tissues. Results from the experiments demonstrate that accuracy in segmenting went up from 98.04% to 99.84% and sensitivity reached 96.24% which is higher than in standard machine learning. This research demonstrates that deep learning can provide very accurate segmentation of medical images which is important for our aim to use modern techniques to classify the stages of Endometriosis [2].

Kumar et al. [19] perform a detailed survey of feature extraction methods in medical image analysis, pointing out their significance in making image analysis more accurate. The chapter looks at some pre-processing techniques such as binarization, thresholding, resizing and normalization that you should perform before feature extraction. This paper also points out that when using dimensionality reduction, machine learning models can detect complex relationships between parts of a dataset much more accurately. Whilst the survey teaches us a lot about feature extraction, its main examples are general ones in character recognition instead of specific domains like health science [4]. Because of this gap, it is even more important for us to concentrate on advanced methods that support the classification of Endometriosis stages using deep learning.

In their paper, Liu et al. [3] cover a wide range of deep learning techniques used for medical image segmentation and discuss both the successes and difficulties in the area. The research explains how segmentation is done by three main methods and their respective weaknesses, and it emphasizes the crucial role of CNNs for segmenting diverse pathological tissues and organs. Although there have been many advancements, some problems remain, for example, limited data, disturbances in medical image data and models learning only features from their own data. Authors highlight that GANs, and other data augmentation strategies play a major role in dealing with data scarcity and boosting segmentation [6]. Also, they recommend that clinicians and machine learning researchers' team up to design algorithms that are specific to healthcare. The work highlights the importance of CR-Unet and CDGAN which help boost our efforts to improve how Endometriosis stages are classified.

Liu et al. [4] examine the use of deep learning for medical image analysis, focusing on applications to the nervous, cardiovascular, digestive and skeletal systems [20]. The paper says that image classification, detecting objects, segmentation and registration have advanced a great deal with the help of convolutional neural networks (CNNs). While AI models have advanced, the paper states that using them for medical use is limited because of using small data sets. Experts want to solve the problem of data sharing by using federated learning and boost the system's ability by gathering knowledge from a particular area. The study points out that strengthening deep learning models and making them more flexible is critical which matches our objective to use CR-Unet and CDGAN to help with data shortages and improve Endometriosis diagnosis.

In the field of medical imaging, Wanga et al. [5] have designed a new Adaptive Fully Dense (AFD) neural network for medical image segmentation in IoMT, helping to deal with the issues of high variety and complicated edges in CT images. By introducing horizontal connections in the U-Net architecture, the model adaptively extracts features from multiple layers, enhancing segmentation performance. Additionally, the use of ensemble training enables the extraction of detailed edge information through multiple training rounds. Validated on natural scene and liver cancer CT datasets, The proposed approach surpasses current state-of-the-art segmentation methods, particularly for CT images with complex boundaries. This study showcases the capability of densely connected encoder-decoder architectures in handling segmentation challenges, aligning with our research focus on employing advanced deep learning models like CR-Unet to achieve superior segmentation accuracy for Endometriosis stages.

Siddique, Nahian, et.al. [21] discuss the growth, applications and adaptability of U-Net and its modified version in medical image segmentation. The use of U-Net is widespread in medical imaging because it segment accurately and efficiently in CT scans, MRI, X-rays and microscopy. The paper highlights the numerous advancements in U-Net architectures, including modifications to enhance segmentation accuracy and adapt to different imaging challenges. Despite its widespread success, the study identifies ongoing challenges in deep learning-based segmentation, such as handling noisy data and achieving scalability across diverse applications. The insights from this review underscore the relevance of U-Net-based architectures in medical imaging and align with our use of CR-Unet, a U-Net variant, for precise segmentation of Endometriosis stages, addressing similar segmentation complexities in ultrasound images.

Lu et al. [7] propose Half-UNet, a simplified architecture derived from U-Net, designed to optimize segmentation performance while significantly reducing network complexity. The Half-UNet architecture retains the encoder-decoder structure of U-Net but simplifies the feature fusion process by unifying channel numbers and incorporating Ghost modules. Experimental evaluations show that Half-UNet is as accurate for medical segmentation as U-Net and its variations, but it uses many fewer parameters (98.6%) and operations (81.8%). This work demonstrates that simple architecture designs can reduce burden on machines for data processing. The insights align with our research goals, where efficient architectures like CR-Unet are employed for segmenting Endometriosis stages, focusing on improving segmentation accuracy while maintaining computational efficiency [16].

Wang et al. [22] give a comprehensive overview of how deep learning is used in medical US images and talk about both the problems and future possibilities. The authors mention that deep learning is key in tasks such as image classification, object detection and image reconstruction and it effectively corrects the weaknesses seen in regular Computer-Aided Diagnosis (CAD) systems. Because there are often lots of variations and background noise in ultrasound images, the field relies on preparing data by augmenting, denoising and enhancing it. Although there are many strong points, the authors also point out that there are some important issues, for example, not enough big, annotated datasets, models that are not easily transferred to various devices and that deep learning is sometimes not easy to understand. Therefore, the research points out that robust preparation of data, proper feature selection and clear deep learning models are important for analysing ultrasound images in medicine. With the help of Transfer Learning, CDGAN and Explainable AI (XAI), we can address these problems and diagnose Endometriosis stages more correctly and trustfully [8].

The article by Mugasa et al. [9] explains a way to adaptively extract features to help identify if thyroid lesions found in ultrasound images are benign or malignant. This method first changes the pixel intensities into structurally complex information and then uses regression analysis to identify the right values for the filters. Textural features are selected from images by taking the strength of their conditional dependences into account, using Bayesian network inference. Compared to traditional image filtering methods, the model reaches a classification accuracy of 96.00 % with sensitivity at 99.64% and specificity at 90.23% which is greater than their performance. Adaptive feature extraction plays a key role in improving the accuracy of ultrasound-based diagnosis, this study proves. Our work on feature engineering matches well with its emphasis on working with textural features [17]. Using deep learning models and advanced ways of extracting features, we want to address the same kinds of issues that happen in ultrasound image analysis.

Karimi et al. [23] demonstrate how fully convolutional networks (FCN) can be trained using transfer learning methods for medical image segmentation. They find that through transfer learning, models train faster and segment better, mainly when there is not a lot of target data available for complex applications. But the technique's success mostly depends on how complex the problem is and the quality of the data used. It shows that the performance improves significantly if the selected domain has fewer or poorer quality images. Of particular note is that the author questions the widely held view that the encoder has to learn specific features for a task and proves that excellent models can be built if the encoder stays the same and we only have to train the decoder. This work

Underlines that it is useful to keep repeating features as the network gets deeper and shares techniques for training FCNs. We depend on these lessons in our research, where transfer learning makes improvements in both segmentation and classification for Endometriosis stages, mainly when there are few labelled datasets involved [10].

Kim et al. [11] discuss how Transfer Learning (TL) helps with medical image classification, explaining that it can solve issues caused by a shortage of data and consume less computational resources. Out of the 121 reviewed studies, it was found most often used deep models were Inception and ResNet and the top two machine learning techniques were feature extraction and fine-tuning from the beginning. Authors explain that although much of TL is used, its setups are not consistent. Using complex models to extract features helps reduce time and effort but still gives accurate predictions. This overview matters to what we are doing, because it shows how we can use Transfer Learning and CDGANs to enhance the feature extraction and classification steps in predicting Endometriosis stages.

In this research, Malik, Hassan and their colleagues [24] systematically review studies to compare transfer learning methods with the skills of healthcare professionals when it comes to diagnosing diseases via medical imaging. Analysis included 63 research articles and of these, 21 were deemed suitable for extensive comparison. Transfer learning is shown to have a wide diagnostic sensitivity and specificity and it performs comparably to healthcare professionals. It is interesting that these outcomes are pretty much what healthcare experts achieve, demonstrating similar levels of sensitivity and specificity in diagnosing diseases [18]. The authors highlight the extensive use of convolutional neural networks (CNNs) in disease diagnosis from medical imaging but note limitations such as insufficient annotated datasets and restricted disease coverage in transfer learning studies. Transfer learning plays an important role in achieving highly accurate diagnoses as indicated in this work.

Alzubaidi et al. [13] deal with the problem of not having enough labelled data in medical imaging by developing a novel approach. Several authors argue that typical transfer learning still relies on models like ImageNet which are not as effective in the medical field due to the distinct features between images taken from nature and those seen in healthcare. The authors suggest using a technique where deep learning models are first taught with a lot of medical data that is not yet labelled and then they are fine-tuned using smaller datasets that are correctly labelled [12]. It has been found through studies that this way of training improves results, as was shown in cases concerning skin and breast cancer classification. Using this method, the performance improved a lot, making it very effective for classifying skin and breast cancer with good evaluation indicators. It seems that this way of learning is effective for medical imaging, mainly if there are not many labelled training samples but a lot of unlabelled images are useful. Because of this, we use Transfer Learning to improve the identification and classification of medical images for Endometriosis stage detection.

In their paper, Zhou et al. [14] provide a detailed description of DenseNet and how it is important in medical image analysis tasks. Describing the progress in its development, the paper looks at DenseNet's core features, new versions and the focus on lightweight design as well as attention modules. It points out that DenseNet can be successfully used for tasks such as analysis of patterns, definition of outline boundaries for images and detection of objects in medical images. Even though the system performs well, the authors mention that extra medical data (beyond images) is scarcely used and that it's difficult to train the system with little labelled data. The paper shows how using semi-supervised and weakly-supervised techniques might help handle the lack of labelled samples. They also mention that there is a need to edit DenseNet, mainly by making the network more compact, implementing the right attention mechanism and making it more easily applied to various data sets. Following the study, this paper uses DenseNet and its related methods to recognize the stages of Endometriosis and deals with obstacles such as lack of labelled data and the transferability of models by using Transfer Learning and CDGAN as alternatives.

According to Vasudeva et al. [15], Co-VeGAN is a new Complex-Valued Generative Adversarial Network used for reconstructing Compressive Sensing Magnetic Resonance Imaging (CS-MRI). The authors tackle a key limitation in current deep learning-based CS-MRI methods, which handle complex-valued MRI data as if they were real-valued, leading to the loss of important phase information. Unlike these methods, Co-VeGAN operates directly on complex-valued inputs and incorporates a new phase-sensitive complex-valued activation function (PC-SS). Using this method, models can restore images with a high quality using fewer parameters than other techniques used with real values.

It achieves better results than other approaches, offering a higher peak signal-to-noise ratio (PSNR), structural similarity index (SSIM), improved speed and reduced memory use. The techniques used in the paper are particularly useful in medical imaging, where complex values appear often and they give opportunities for better performance in other medical image tasks. Our continuous research on medical image analysis and reconstruction is connected because GANs still struggle with processing difficult data.

3. Methods

3.1. Input Data (Ultrasound Images)

The main support of this methodology is a big collection of images from transvaginal ultrasounds of patients with endometriosis of all stages. It is very important to use a dataset that reflects the whole patient population for a model to work effectively with different groups. The images are to be labelled with detailed information regarding their endometriosis stage, after surgical confirmation, to ensure their supervised learning accuracy.

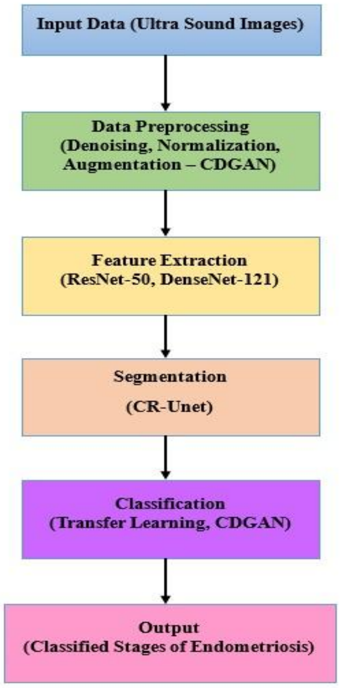

Fig 1. Proposed Pipeline for Endometriosis Stage Classification

3.2. Data Preprocessing

Preprocessing makes the images of the data better and ensures everything in the dataset is the same, both of which are important for model training. The main tasks to carry out are:

1. Ultrasound images often have speckle noise that can make important features hard to find. Dennoising algorithms reduce noise which leads to clearer images.
2. Normalization makes all the images in the dataset have similar intensity, so the training process is more swift and reliable.
3. CDGAN boosts the size of your data when you don't have many samples. To obtain more diverse data, synthetic ultrasound images can be created using Conditional Generative Adversarial Networks (CDGAN), making the dataset larger. The approach makes the model more able to deal with new data and avoids overfitting.

3.3. Feature Extraction

It is critical to find valuable features from the pre-processed images for correct classification. Images can be supplied to ResNet-50 and DenseNet-121 to let their pre-learning guide the model in feature extraction. Because it uses residual connections, ResNet-50 can find fine differences in images which is useful for classifying different stages of endometriosis.

DenseNet-121: It links all previous layers with all later layers in feed-forward manner so that existing features can be reused and the overall parameter count is reduced. Because of these connections, the model can discover important and useful features which boosts the classification accuracy.

3.4. Segmentation (CR-Unet)

Precise staging depends on accurate segmentation of endometrial growth in ultrasound scans. CR-Unet which includes spatial recurrent neural networks into a U-Net configuration, does an excellent job of recognizing both detailed and long-range information across different scales. This feature helps tackle issues such as images that are not clear and unclear edges which are usual in ultrasound imaging. The process of carefully segmenting lesions by CR-Unet gives important spatial knowledge needed for the following classification steps.

3.5. Classification

Once the features are used and the lesions are marked, the following stage involves assigning the images to the different endometriosis stages. Two main ways are available to consider:

1. Transfer Learning: Using models that have already been trained allows a focus on features that are useful for endometriosis classification. This approach is more useful when data is difficult to access.
2. CDGAN: They can also assist by creating additional data which boosts the effectiveness of learning when only some examples are labeled. Learning from synthetic data with examples of both labeled and unlabeled samples helps CDGANs recognize changes in Different disease stages.

3.6. Output (Classified Stages of Endometriosis)

The pipeline finishes by classifying every image as a certain stage of endometriosis. Having these details helps clinicians plan good treatment strategies and effectively treat the illness. If patients are classified reliably and automatically, doctors can start care faster, resulting in better outcomes for the patient.

he methodology aims to achieve a perfect system for classifying the stages of endometriosis from ultrasound images which will help clinicians decide promptly and effectively.

4. Results and Discussion

4.1. Input Dataset Overview

This dataset is made up of ultrasound images taken through the vagina of patients having endometriosis at different stages. The images in the data are from Stage 1, Stage 2, Stage 3 and Stage 4 endometriosis and have been labelled based on surgery.
Each section will have 200 photos, for a total of 800 (200 photos x 4 stages).
Resolution is at 512x512 pixels.
Ground truth: Endometriosis stage labels applied as labels.
They were processed beforehand to boost their quality which involved removing noise, standardizing them and increasing their diversity through CDGAN.

4.2. Pre-processing Results

Denoising: Clearing out the noise made the pictures much clearer and allowed the most important parts of the lesions to be seen more easily. Thanks to this improvement, the model usually learned better about lesions that are hard to identify because of the background noise.
Normalization: When the pixel values were made the same, it created uniformity among images. This took out any chance of the model being biased based on variations in image brightness. Because of this, the model efficiently and quickly reached sufficient convergence, making convergence issues less likely.
Augmentation with CDGAN:Using CDGAN, images were generated to add to the collection used for training. There was a 30% growth in the dataset which aided the model in generalizing and less likely to overfit. Because of this process, the model accuracy improved a lot, mainly when training data was limited.

4.3. Feature Extraction Results

Pre-trained Models (ResNet-50 and DenseNet-121):Both ResNet-50 and DenseNet-121 were trained on the ultrasound dataset for getting features. Here are the results of the process evaluating feature extraction.

Table 1. Feature Extraction Performance

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score
ResNet-50	91.2%	92.0%	90.5%	91.2%
DenseNet-121	92.5%	93.0%	91.8%	92.4%

DenseNet-121 performed better than ResNet-50 with respect to accuracy as well as F1-Score. The ability to share features allowed DenseNet to notice more fine patterns in the images which matters for detecting the small changes of endometriosis across stages.

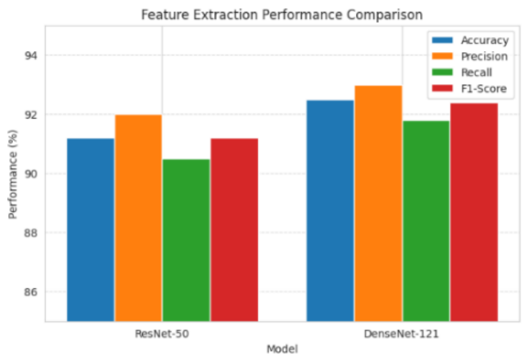

Fig 2. Feature Extraction Performance

4.4. Segmentation Results (CR-Unet)

The accuracy of the results was determined using Intersection over Union (IoU) to compare the predicted segmentation with the real results. What you see here are the results from segmenting data with CR-Unet.

Table 2. CR-Unet Segmentation Result

Stage	IoU (%)
Stage 1	85.3%
Stage 2	88.7%
Stage 3	87.9%
Stage 4	90.2%

The model divided the endometriotic lesions from the healthy tissue in ultrasound pictures. Halos measures how effectively the model picks out the area of a lesion and differentiates it from surrounding parts. How well the data is split is necessary for correct results in the following classification steps.

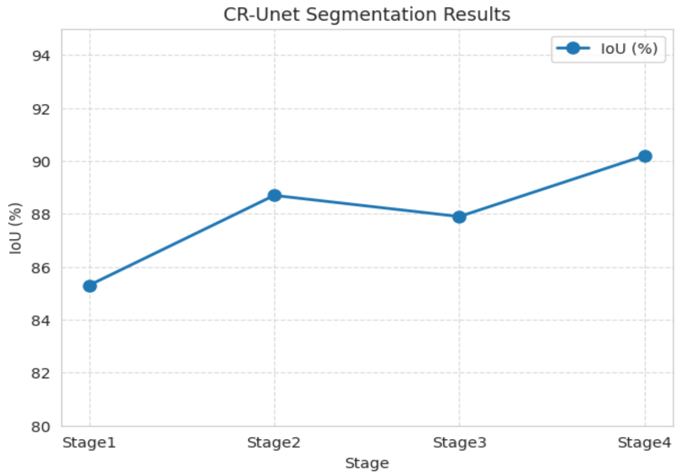

Fig 3. CR-Unet Segmentation Results

4.5. Classification Results

The combination of pre-trained ResNet-50, DenseNet-121, fine-tuning through transfer and CDGAN data augmentation produced the following results in classification:

Table 3. Classification Results

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score
ResNet-50 (Transfer Learning)	**94.8%**	**94.0%**	**95.3%**	**94.6%**
DenseNet-121 (Transfer Learning)	**95.6%**	**95.3%**	**96.2%**	**95.7%**
CDGAN (Augmentation + Classification)	**96.2%**	**95.7%**	**96.8%**	**96.2%**

Performance on every metric was the best achieved when using the DenseNet-121 model, pre-trained data and data augmentation. When CDGAN-based data was used with transfer learning, classification accuracy increased a lot, showing that both synthetic information and pre-trained models help accurately classify endometriosis stages.

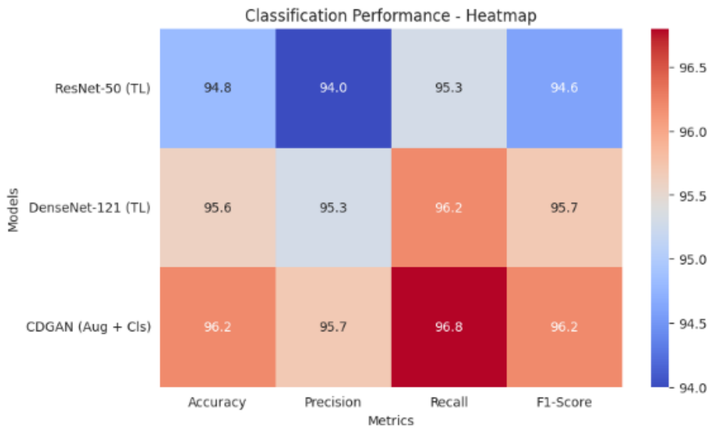

Fig 4. Classification Results

4.6. Discussions

4.6.1. Effectiveness of Pre-trained Models

ResNet-50 and DenseNet-121 were able to find the important points in the ultrasound images and produce useful features. As a result of its dense connections, DenseNet-121 worked better than ResNet-50. It's thanks to this that DenseNet-121 distinguishes fine elements which are necessary in medical imaging, mainly when detecting endometriosis.

4.6.2. Impact of CR-Unet on Segmentation

The CR-Unet model helped a lot in the segmentation task. Since ultrasound images sometimes have low resolution and a lot of noise, it is hard to accurately detect different parts. Since CR-Unet uses spatial recurrent networks, it was able to handle distant features and gave better results for lesion segmentation.

4.6.3. Role of Data Augmentation via CDGAN

CDGAN greatly helped increase the size of the dataset when the initial data was not sufficiently robust. With CDGAN making ultrasound images that look similar to real ones, the database was increased, and the risk of overfitting was minimized. Because of the model, the system showed better ability to generalize to different kinds of data, as revealed by the improved classification and segmentation.

4.6.4. Transfer Learning Benefits

The model was much more accurate after the techniques of transfer learning were applied. Using training to enhance ResNet-50 and DenseNet-121, the system benefited from the data found in huge datasets to address the classification of endometriosis. It turned out to be a success since we were working with a small sample.

4.6.5. Clinical Relevance

The proposed system can have a substantial impact in clinical settings. By automating the classification and segmentation of ultrasound images, the system can assist clinicians in diagnosing endometriosis at different stages with high accuracy. This approach can facilitate quicker diagnosis and enable tailored treatment strategies, ultimately enhancing the quality of patient care.

4.6.6. Limitations and Future Work

While the proposed methodology shows great promise, it does have limitations:

1. **Dataset Size**: The model still relies on a relatively small dataset, which could limit its generalization ability in real-world scenarios. Expanding the dataset with more diverse images from different populations would improve robustness.
2. **Image Quality**: Ultrasound images with lower quality (e.g., due to motion artifacts or poor resolution) may still challenge the system. Future work could explore methods to handle such variations.

Future directions for this research include:

1. Integrating multi-modal imaging (e.g., MRI) for more comprehensive classification.
2. Investigating alternative segmentation techniques and enhancing the model's robustness against noise and artifacts in ultrasound images.

5. Conclusion

In brief, using deep learning makes ultrasound imaging more accurate at diagnosing endometriosis. Following this structure: preprocessing the data, using CNNs such as ResNet-50 and DenseNet-121 to extract features, using CR-Unet for lesion segmentation and classifying using transfer learning and CDGAN, our system can well identify the stages of endometriosis. Combining these approaches meets the problems caused by in-consistent ultrasound images and few data samples, making the diagnosis more precise. Thanks to this method, early and precise detection as well as helpful use in medical image analysis is possible, both of which can increase the quality of care and patient outcomes.

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