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The Application of Artificial Intelligence Technology for analysing MRI images of uterine fibroids – the difficulties and limitations

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Abstract

MRI (Magnetic Resonance Imaging) is now frequently used to diagnose uterine fibroids and to determine the treatment approach for minimally invasive surgery and non-invasive focussed ultrasound (HIFU) surgery. However, MRI images of some fibroids can be difficult to identify accurately. In this paper, we explain in simple terms the approaches used in the Artificial Intelligence (AI) study of MRI imaging that can analyse, learn, and increase the sensitivity of determining the sizes, locations, number of fibroids, and their abnormalities. The difficulties and limitations of AI application to automatic analysis of MRI fibroid images in our early study are discussed. This paper hopes to arouse the interest of medical professionals to understand how the mechanism of AI can help analyse MRI images and incorporate AI into their daily imaging work.

Keywords: Magnetic Resonance Imaging, MRI, Artificial Intelligence, AI, uterine fibroids, segmentation, deep learning, deep neural networks, DNNs, convolutional neural network, CNN, Transformer

Introduction

Uterine myomas (fibroids) affect 70% of reproductive-aged women, and they impact their health and fertility. It is often suspected by detecting an enlarged uterus with menstrual disorders. Ultrasound scan is commonly used to diagnose and determine the treatment approach. However, ultrasound scans are highly skill-dependent and sometimes difficult to determine the fibroids' positional relationship with the uterine cavity and wall and define the exact number of fibroids. MRI is now frequently used, gives better-resolution images, and is not skill-dependent. However, the complex and variable shapes of fibroids and the low contrast between fibroids with adjacent uterine tissues or pelvic organs make the edges of some fibroids indistinguishable from their surroundings. Therefore, MRI images of some fibroids can be difficult to identify accurately. Artificial Intelligence (AI) simulates human thinking and can analyse and interpret complex medical data. Hopefully, the application of AI in MRI imaging may increase the sensitivity of detecting fibroids and their abnormalities. AI may also reduce interobserver variance and improve report consistency. This paper will address the methodologies used by computer scientists in AI imaging analysis and the difficulties and challenges in developing an automatic AI model to identify and localise uterine fibroids.

Methodology

To develop a proposed AI model for MRI images of fibroids; it is expected to study;

1. An adequate number of relevant MRI images from patients recruited and agreed to participate in the study for AI machine learning
2. The MRI images of fibroids are first digitalised, enhanced, and pre-processed.
3. The fibroids' images for each patient will undergo segmentation by AI model.
4. The salient fibroid features are extracted for automatic analysis and studied by machine learning.
5. Segmentation and classification of these images will be automatically performed using Deep Neural Networks (DNNs), which enables AI to learn by studying and analysing a large number of data from a large database of MRI fibroid images.

After our preliminary study with a small number of patients, we feel the need for more clinicians or radiologists involved in the study and more understanding of AI technology. The application of AI in MRI imaging involves the following computer procedures to develop the AI model for MRI image analysis: (1) medical image segmentation, (2) Deep learning, and (3) various Deep Neural Network techniques to learn and analyse MRI images of uterine fibroids.

(1) Medical Image Segmentation

Medical image segmentation is a commonly used technique that helps to concentrate on key regions for medical image analysis (Figure 1). Many medical image segmentation methods have been proposed (1-5). With the development of AI, existing state-of-the-art methods are mainly based on the Deep Learning (DL) approach. It collects a large number of medical images and trains a strong AI model for automatic segmentation. However, experts or medical doctors must first annotate a reasonable number of MRI images to train an AI model.

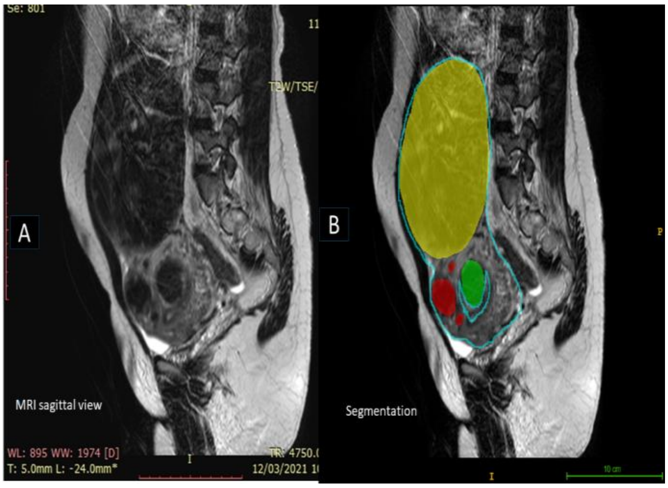

Figure 1. A. Sagittal MRI T2WI image of a uterus with multiple fibroids B. Segmentation of the uterus and fibroids were annotated by an expert to identify the uterus and the locations of all fibroids, allowing AI programs to study and learn.

As described in papers by Zhang et al. 2020, Niu et al. 2021, and Tang et al. 2020, automatic AI segmentation follows various medical image segmentation pipelines, which collected hundreds of annotated fibroid cases, then trained a Convolutional Neural Network (CNN) model to segment the uterus and fibroids simultaneously (6-8). Specifically, Zhang et al. proposed HIFUNet for multi-class segmentation of uterine regions and myomas (9). Niu et al. used the Hessian matrix to extract image edges (7). They both can complete the image segmentation of uterine MRI automatically. Tang et al. proposed AR-UNet for automatically segmenting uterine myomas from T2-weighted MRI images (8). Although promising results have been demonstrated, they all reported difficulties in performing accurate segmentation results due to the lack of sufficient annotated fibroid cases. In addition, to explore the complex fibroid features, more advanced AI techniques and modified DNN architectures might be required.

(2) Deep Learning

Traditional medical image analysis requires tedious efforts of experts and radiology doctors. To address the problems of low efficiency of humans, Deep learning (DL) has been widely employed in many tasks of medical image analysis, including analysing medical image segmentation (10) and classification (11).

Deep Learning (DL) was proposed by three famous scientists, Lecun, Bengio, and Hinton in 2015 (12). Rumelhart et al. used the back-propagation method to update the parameters of Deep Neural Networks (DNNs) during training (13). The training process includes three parts: (1) Input a large-scale dataset into the DNNs and output the predictions; (2) Design a "loss function" data to calculate the disparity between the predictions and the ground features annotated by experts or doctors in these MRI images; (3) Update the parameters of DNNs by back-propagation with the loss function. Specifically, back-propagation is a mathematical optimisation tool to update the parameters of DNNs, which enables it to train itself into a powerful AI model by continuously inputting large-scale data into the Deep Neural Networks for machine learning. As shown in Fig.2, it describes the pipeline of DL for medical image analysis, including data collection, data annotating, and model training.

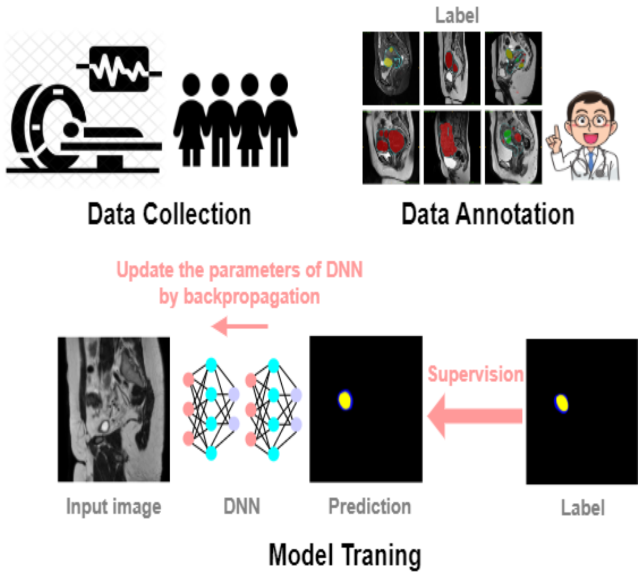

Fig 2. The pipeline of DL for medical image analysis includes three stages, i.e., data collection, data annotation, and model training. The process of expert supervision and back propagation is introduced to update the parameters of DNNs, which enables it to train itself by continuously inputting large-scale data for machine learning. (Drawing from Wu, Qiu and Chen)

Therefore, the key to the success of Deep Learning includes two important parts: (1) a high-quality and large-scale annotated dataset and (2) a well-designed deep learning model to learn the knowledge from the dataset.

Our early results revealed the difficulties and limitations after feeding DNN with a small learning sample before we study how DL can leverage large-scale data to train a model in medical image analysis in our future MRI study.

Neural Network techniques – the Deep Neural Networks

Within the Deep Neural Networks (DNNs), Convolutional Neural Networks (CNN) (14, 15) and Transformers (16) are two of the most widely used computer DNN architectures currently.

Convolutional Neural Network (CNN)

Convolutional neural network (CNN) models have been successfully applied by Yamashita et al. 2018 to study a wide range of radiology images, including detection, automatic segmentation of lesions, and image classification (14, 15, 17). Zhang et al. 2020, Niu et al.2021, and Tang et al. 2020 demonstrated the learning ability of CNN models to detect fibroids in the region of interest with high accuracy (7-9).

With the powerful ability to extract local features, CNNs can perform better by focusing on the most informative part and analysing lesions. As shown in Fig.3, we present the process of CNNs to extract medical image information. The architecture of a CNN consists of different layers that work together to extract meaningful features from images.

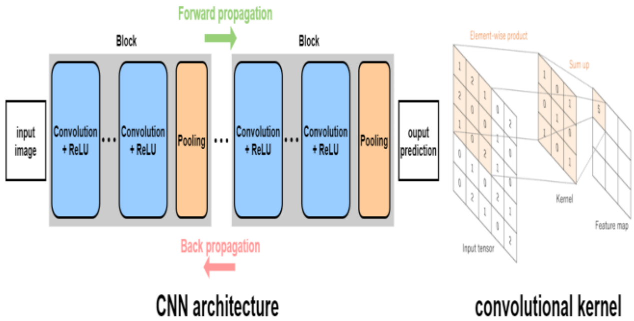

Fig.3 The typical architecture of CNN and a convolution kernel: The process of CNNs is to extract information from input medical images. Details of this architecture are described in (Krizhevsky et al., 2012; He et al., 2016; Yamashita et al., 2018).

The main advantage of CNN models is their capability to extract highly specific features using a data-driven approach. It allows managing fewer parameters effectively and resilience to data augmentation during training. Overall, CNNs allow the extraction of highly specific features from visual data. This capability makes CNNs effective in tasks like image recognition, object detection, and image classification.

CNN is frequently used for medical image segmentation and has proven to be successful in medical image segmentation:

Although promising results have been demonstrated, existing CNN models have a more restricted capacity for smaller regions. Therefore, it appears to be a difficult task for CNN models in multiple small fibroid lesions. CNNs use filters that slide over the input image to capture features. However, if a lesion is very small, it may not be fully covered by the receptive field of the filters. This means the CNN might not gather enough information about the lesion to detect it accurately, making it difficult for the CNN to capture and recognise small lesions.

Transformer

Transformers are proposed to capture global information, which has also been employed in medical image segmentation (18, 19). In medical images, some features may heavily relate to other regions, e.g., the analysis of tumours requires us to recognise the organs in the meantime. Thus, we must leverage global and local information in medical image analysis. Transformers employ a novel attention mechanism to model the global and local relations, enabling us to improve analysis accuracy. As shown in Fig.4, we present a typical Transformer architecture for medical image analysis.

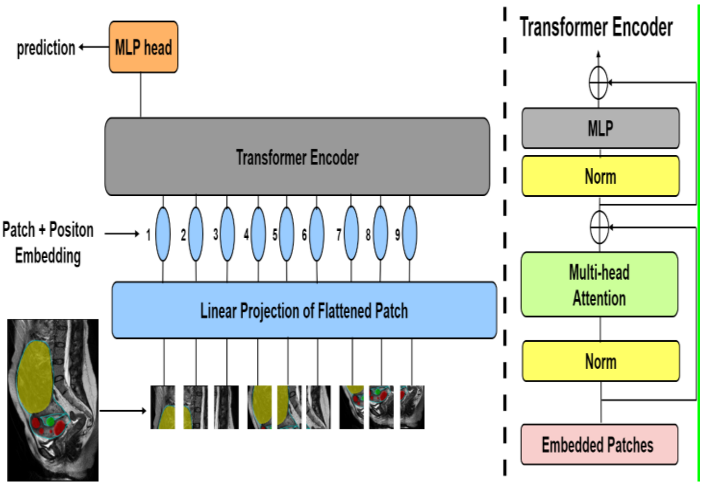

Fig.4 The typical Transformer architecture (Dosovitskiy et al., 2020). Multilayer Perceptron is termed as MLP. The input image is first patchtified as several equal size patches then flattened and input to the Transformer encoder. The key module in the Transformer encoder is the Multi-head Attention described by Vaswani et al. 2017 (20), which uses an attention mechanism to aggregate global and local features.

The Transformer architecture was originally designed for natural language processing. It has also been adapted for computer vision tasks (16). Here is a simple explanation of how the Transformer works in computer vision:

1. Patch Extraction: The MRI input image is divided into smaller patches or regions. Each patch represents a local area of the image.
2. Encoder: The patches' embeddings are passed through an encoder. The encoder applies self-attention to the patch embeddings, allowing the model to capture relationships and dependencies of information between different patches. This helps the model understand the global information within the image.
3. Decoder: The decoder takes the encoded patch embeddings and generates a prediction or output.

Transformer consists of Multilayer Perceptron (MLP), Norm (Normalization), and Multi-head Attention. (a) MLP is a type of neural network architecture that consists of multiple layers of interconnected nodes (neurons) to process and transform input data. In Transformers, MLPs are typically used as feed-forward networks to process and extract features from the input data, such as image patches. (b) Norm is a technique to standardise and normalise the input data values. It ensures that the data falls within a certain range, making it easier for the model to process and learn from (c) Multi-head Attention is a key component of Transformers that allows the model to capture different types of relationships between input elements. It splits the input into multiple parts and applies attention mechanisms to each part separately. By doing so, the model can capture features to allow a more comprehensive understanding of the relationships and dependencies within the data.

The Transformer has proven effective in medical image segmentation, which involves identifying specific structures in medical images (18, 19, 21). It is good at understanding the relationships between different parts of the image, making it useful for accurately delineating irregularly shaped structures. The Transformer can benefit from pre-training on large datasets, improving its ability to segment structures and assist medical professionals in diagnosis and treatment.

Difficulties and Solutions from the initial study

The early study involved MRI images from 30 cases of fibroids and adenomyosis. Our early experience of this AI driven MRI analysis meets many difficulties and challenges. They are

(1) An expert or radiologist must do the tedious work to identify and mark out fibroid/s in the digitalised MRI images for accurate segmentation information to offer a successful outcome to analyse the specific lesion in the MRI images. It may require experts to contribute annotated MRI images of up to several hundred or a thousand

cases to improve the accuracy of machine learning. We anticipate the expertise and time involved would be very expensive as a research project.

(2) The limitations of the AI analysis of MRI images for uterine fibroids involve (a) MRI images obtained from various MRI machine systems with variations in scan parameters. Therefore, the training data set can be variable with different MRI parameters. (b) Digitalised MRI images require considerable resources and computational power to analyse the various features of fibroids, thus posing a challenge to the scant resources in medical practice and expertise in the field. Besides, to train a DNN model for automatic MRI analysis, adequate large MRI images from patients and the corresponding correct labels from experts are required. Collaborating with a large medical centre or multiple centres is necessary to have a large-scale MRI fibroid dataset.

(3) Many other abnormalities exist in the fibroid MRI images, such as border irregularity, degeneration, variation of signal intensity, and vascularity, which present inconsistent appearances. Therefore, AI medical imaging applications have great computing difficulties for uterine fibroids.

(4) Medical segmentation of uterine fibroids had been difficult because a clear, sharp boundary of a fibroid is hard to obtain, especially with complex and diverse shapes and irregularity of fibroid, poorly contrasting with tissues or organs surrounding it.

(5) It would be difficult to differentiate fibroids from sarcoma or other abnormal pelvic organs. Often, small sample sizes and non-validated AI models are the main limitations in this field of research on fibroids. Therefore, a large enough database for fibroid MRI images will allow continuous machine learning that can help AI image analysis reach the expertise of an experienced radiological expert.

(7) Further studies are required to find suitable AI computing techniques, such as improved convolutional neural networks or transformers, to allow automatic and accurate characterisation and classification of uterine fibroids with high precision.

(8) Finally, adequate validation studies in many medical centres will be necessary to confirm these various AI models and determine their feasibility, accuracy, and efficiency. It is a long-term ongoing project that requires adequate enthusiasm and financial support to enable AI applications to be used in the MRI analysis of fibroids.

Discussion

Uterine fibroids can be single or multiple, small or large, with heterogeneity within a fibroid. The sizes and locations of a fibroid can cause various symptoms like heavy menstrual bleeding, pain, bladder irritation, constipation, miscarriage, or obstetrical complications. A radiology expert will take many years of training to achieve an expert's accuracy and efficiency in diagnosing uterine fibroids. On the other hand, once an AI-driven model is established, a computer MRI image analytic model is expected to achieve the same expertise very effectively. It will not suffer tiredness as in a human expert and can extend its working hours, improving accuracy and efficiency using AI learning.

Another advantage of an automatic AI model is that it can also help to reduce interobserver diagnostic variations and improve accuracy and reproducibility. Using computer analysis of uterine fibroids, not only can the sizes, shapes, and locations of fibroids be determined, but any atypical appearances can be differentiated and may lead to the diagnosis of potential cancerous lesions.

At present, doctors can hardly understand many computer AI terminologies. Computer scientists have more advanced computing knowledge, but without knowing the clinicians' need to require an AI-driven model. Therefore, most clinicians will find it hard to collaborate with computer scientists to develop an AI model seamlessly and quickly to effectively and accurately meet clinical use.

This paper hopefully lets doctors understand and arouse their interest in how the above computer analysis can be achieved to detect fibroid in uterine MRI images. Some AI researchers have successfully applied the convolutional neural network models to study breast (11), Colorectal (22), brain disease (10), and cytological screening. Based on the learning ability of the DNN network and deep learning technology, the computer can improve its localisation of regions of interest (ROI) with high sensitivity, rendering clinicians alerts of atypical findings in the MRI images.

Conclusion

Deep learning and machine learning AI techniques will surely provide radical changes to diagnose and evaluate many uterine fibroid features in the future due to their ability to rapidly study and analyse a vast amount of data and automatically characterise them accurately and quickly.

In this article, we tried to allow doctors to understand AI technology with limited computer terminologies used to develop an AI model to diagnose and evaluate the various MRI features of uterine fibroids. Although many AI models nowadays exhibit an impressive capability for accuracy, efficiency, and learning ability, their deployments are limited to a small number of individual medical areas. There is a call for new AI model studies to allow their applications even in resource-restricted centers or countries. AI-driven models in MRI image analysis can become a cost-effective, accurate, and time-saving tool for radiologists to report and diagnose abnormalities. Further development into other radiology areas in routine healthcare services can be beneficial and reduce the need for radiology expertise workforces.

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