Dean&Francis
ISSN 2959-6157

Research on artificial intelligence-assisted magnetic resonance imaging: a review

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Abstract:

Magnetic resonance imaging (MRI) has been widely used in clinical diagnosis since its introduction with its high resolution and unparalleled contrast imaging of soft tissues. The traditional MRI image analysis is highly dependent on subjective judgment and has the risk of misdiagnosis. The efficiency of human relied diagnosis is still needs to be improved. In recent years, artificial intelligence technology has developed rapidly and gradually involved in MRI image analysis. For example, the image segmentation algorithm, machine learning and deep learning are increasingly widely used in MRI image processing. This paper explores the use of traditional machine learning and deep learning models in MRI and focuses on their ability to extract advanced features, and performance of lesion detection and tumour classification. The advantages and disadvantages of traditional machine learning models such as support vector machines (SVM) and random forests (RF) and their applications are discussed. The deep learning models, particularly convolutional neural networks and generative adversarial networks, this paper focus on their principles and applications to assist MRI diagnosis.

Keywords: Medical device; machine learning; deep learning; MRI.

1. Introduction

Since its introduction in the 1970s, MRI has gained widespread adoption in clinical medicine, leveraging its strengths of exceptional spatial resolution, versatile multi-parameter imaging capabilities, and unparalleled soft tissue contrast for enhanced diagnostic accuracy. However, the traditional MRI image analysis and diagnostic process is highly dependent on the doctor's experience and subjective judgment. There are still some problems such as the risk of misdiagnosis caused by fatigue [1-3].

In recent years, complex MRI imaging data can be analysed by machine learning (ML) and deep learning (DL) algorithms because of the continuous development of artificial intelligence technology. The advanced algorithm model can achieve fast and accurate MRI image segmentation, lesion detection and classification. The traditional image analysis system is usually regarded as a statistical model or machine learning model that works by processing features in an image region that range from low level image features such as edges or corners to high-level

ISSN 2959-6157

image attributes such as textures. However, modern deep learning models utilize convolutional neural networks (CNN) and generative adversarial networks (Gan). CNN extracts local features and spatial relationships from images through structures such as convolution layer and pooling layer, which is suitable for segmentation and classification of MRI images. GAN can generate realistic MRI images or repair images through the adversarial training of generator and discriminator. The rapid development of this convolutional neural network has promoted the wide application of deep learning in MRI image analysis[4,5]. The DL models with high accuracy usually involve a lot of convolution, computation and feature extraction due to their potentially complex nonlinear structures [6,7].

The lesion detection and classification are one of the important tasks in MRI diagnosis[8]. MRI is mainly used in the diagnosis of brain diseases and other soft tissue areas. This technique is able to show in detail the anatomy and tissue properties of the brain, making it a powerful tool for detecting and locating tumours. The image segmentation and reconstruction are key steps in MRI image processing for lesion detection and classification. Image segmentation can transform complex images into regions or objects that are easier to process and extract representative features, and aim to assist the AI model to separate different tissues and diseased areas in the image. These features can be used as inputs for classification algorithms to train classifiers and improve classification accuracy. Traditional image segmentation usually depended on manually set edge detection algorithms thresholds that is difficult to process complex MRI images. The deep learning algorithms can automatically learn feature representations in MRI images to achieve accurate image segmentation [8].

2. IMAGING PROCESSINGF FOR SEGMENTATION

The segmentation algorithm divides the image into different, non-overlapping regions. The core idea is to divide data or information into subsets or regions according to certain rules or characteristics. There are several common traditional segmentation algorithms as following:

Threshold based segmentation: This method divides pixels or voxels in different areas of the image into different categories by setting one or more thresholds. The selection of the threshold is usually based on the grayscale distribution of the image. A single threshold value is often difficult to obtain a satisfactory segmentation effect.

Region based segmentation: Region segmentation according to the image is divided into multiple subregions based on the similarity of pixels or regions in the image. These subregions usually have similar characteristics such as grey scale, texture, brightness and have continuity within the image. Region-based segmentation algorithms mainly include region growing and region splitting merging method. Region-growing method usually starts from a set of ‘seed points’ by attaching a region pixel with similar properties to the seed to each seed in the growing region. It gradually expands the region boundary until some stopping condition is met. The region splitting and merging method treats the image as a whole. The final segmentation result is formed by recursively splitting the region into smaller subregions and then merging similar subregions.

Edge based segmentation: Edge based segmentation algorithm realizes segmentation by detecting edge in image. Edges are the boundaries between different areas of the image. It also usually manifests as a sudden change in grey scale or texture features. However, edge detection is often difficult due to the noise and fuzz in MRI images [9-11].

In addition, deep learning techniques are also applied to segmentation. Different from traditional algorithms, DL algorithm trains a deep neural network model to automatically learn the feature representation in the image and implement the segmentation task accordingly. U-Net is a classical algorithm widely used in biomedical image segmentation. The algorithm structure is composed of symmetric encoder and decoder, and a jump connection is added in the middle. The encoder gradually reduces the size of the feature map and extracts multi-scale features through convolution layer and pooling layer. The context information captured by the encoder provides global awareness. The decoder gradually recovers the size and information of the feature map by transposing the convolution layer, and fuses with the corresponding layer of the encoder to gradually restore the image details. In addition, a jump connection is established between the encoder and the decoder. Transfer high-level semantic information from the encoder to the decoder to help recover details and edge information. Full Convolutional network (FCN) is one of the first algorithms applied to image segmentation in deep learning. FCN removes the full connection layer in traditional CNN, and adds a transposed convolutional layer so that the network can accept input images of any size and output the segmentation results of the corresponding size. It usually uses a pre-trained CNN as a feature extractor and extracts image features through multiple convolution layers and pooling layers. The transposed convolution layer can enlarge the size of the feature map and make it the same size as the input image. In order to fuse features of different resolutions, FCN also introduces skip joins to fuse low-level and high-level features. The last layer of the FCN model uses a 1×1 convolution layer to map each pixel point to different categories and generate segmentation results to complete pixel classification.

3. TRADITIONAL MACHINE LEARNING FOR MEDICAL DIAGNOSIS

3.1 ML Applications and Targets

Feature engineering-based classifiers for classification tasks: Machine learning relies on prior knowledge and artificial feature extraction to detect brain tumours or other organ abnormalities, often based on shape, texture, and intensity features in MRI images. Machine learning classification algorithms use classifiers such as Support Vector Machines (SVM)and Random Forest (RF), which classify different classes of MRI images such as images of normal and diseased tissue by constructing hyperplanes. For example, using SVM to distinguish brain tumours from normal brain tissue, or to identify different types of tumours (e.g., glioma, meningioma). SVM is used as a classifier to train the extracted features and facilitate the construction of a model for detecting tumour types. This method can achieve classification accuracy of up to 90%, especially on small data sets. SVM is strong in classification performance, generalization ability, and robustness. This algorithm is especially suitable for MRI image classification tasks with high feature dimensions, so the classification effect of brain tumours is very significant. Random forest is an ensemble learning algorithm, which improves the stability and accuracy of classification by integrating multiple decision trees. For tumour detection and classification, RF can be used on MRI images with different relaxation (T1, T2). RF is suitable for processing complex and multimodal MRI data, especially when processing multiclass classification tasks[9].

Machine learning is a very important step in the development of traditional artificial intelligence. The process of medical diagnosis using ML are showing by the following steps:

Data collection and preparation: Data acquisition is scanned using advanced MRI equipment to obtain high-resolution images. These images contain a wealth of soft tissue information. The acquired original MRI images also need to be denoised, normalized and normalized pre-processing steps. Ensure that the image parameters are set consistently to facilitate subsequent analysis and comparison

Choose an algorithm: Select the appropriate machine learning algorithm according to the requirements of the diagnostic task. For example, the CNN, Support Vector Machine (SVM), which perform well in the field of image processing.

Build and train the model: The training set was selected from the existing MRI image database. These images contain known disease labels in order to learn the characteristics of the disease. In order to ensure the accuracy of ML model in predicting disease type and severity, and thus improve its overall prediction ability, it is necessary to fine-tune the model parameters.

Model evaluation and make prediction: Evaluate the accuracy and reliability of established models to ensure that models can be used for further predictions. The model classifies the extracted MRI image features and gives corresponding diagnostic suggestions and basic predictions.

continual optimization: Collect feedback on the accuracy and reliability of the diagnostic results, adjust the model parameters according to the feedback results, introduce new features and improve the algorithm to improve its diagnostic performance[9].

3.2 DL Applications and Targets

MRI image processing based on deep learning algorithm: The Deep learning algorithms are widely used in feature processing and feature recognition in the field of medical imaging. Convolutional neural networks are suitable for image classification and feature extraction. In MRI image analysis, CNN is able to automatically extract high-level features from images, unlike the steps of manually designing features in traditional machine learning. The U-Net network is widely used in tumour segmentation of MRI images, which can accurately capture local details and is especially suitable for processing pixel-level accurate segmentation tasks. The Generative adversarial networks (Gans) are used in MRI image analysis for data enhancement and image repair. GAN can transform low-resolution MRI images into high-resolution images, improving the clarity and detail of the images. The sample set can be expanded by synthetic data to improve the performance of the model when the data is limited. In general, the application of deep learning algorithm in MRI image feature processing and feature recognition mainly focuses on automatic feature extraction, segmentation and classification.

The artificial intelligence deep learning techniques work by simulating the human brain and creating decision-making patterns. DL is a branch of machine learning that automatically learns useful representations and features from raw data. It builds and trains deep neural network models to learn and extract features from large amounts of data to automate complex task processing and decision making.

ISSN 2959-6157

The process of deep learning and machine learning for MRI image diagnosis is roughly similar. Unlike traditional machine learning models, deep learning models are often more complex with multiple hidden layers that can learn deep features of the data. In the field of medical imaging, the interest in deep learning is primarily sparked by CNN. The conventional CNN is a specialized type of artificial neural network designed to preserve spatial relationships within data, featuring sparse connections between layers with multiple layers of convolution and activation. These layers are typically interspersed with pooling layers, and, like standard artificial neural networks, CNNs are trained using backpropagation and gradient descent. Furthermore, CNNs often conclude with fully connected layers, which are responsible for computing the final output. Here are the building blocks of CNN [12]:

For the Convolutional layers: In the convolution layer: In the convolution layer, the input data is usually a two-dimensional or three-dimensional array (MRI image), while the convolution kernel (filter) is a smaller two-dimensional or three-dimensional array. Convolution checks scan the input data and generate feature maps by adding products by element. The size of the convolution kernel determines the efficiency of feature extraction. The size of the convolution kernel is usually much smaller than the input data, usually 3x3, 5x5. The step size affects the size of the output feature map. The larger the step size, the smaller the size of the output feature map. In addition, the filling technique is also used in the convolution layer to avoid the loss of edge information during the convolution process, and to help keep the input and output sizes consistent.

Activation function layer: The activation function layer usually follows the convolutional layer, which transforms the input using nonlinear activation functions. Common activation functions include ReLU (Rectified Linear Unit), sigmoid, and tanh. Its characteristic is that when the input value is greater than 0, the output is equal to the input; When the input value is less than or equal to 0, the output is 0. The function is $ReLU(x) = max(0,x)$. The function has fast convergence speed, no saturation interval and high computational efficiency. After transforming the activation function, the output of each layer of the neural network can be regarded as the characteristic representation of the input data. These feature representations are further processed and abstracted in subsequent layers to form higher-level features. In general, the role of the activation layer is to enable CNNS to learn nonlinear relationships in the network to better process and analyse complex data.

Pooling: Pooling is mainly used to reduce the dimension and complexity of the feature graph, and reduce the computation and parameter number of the network (dimensionality reduction). The pooling operation splits the input feature map into multiple non-overlapping subregions, and then performs a specific operation on each subregion to obtain an output value that represents the subregion. The pooling workflow is as follows:

Determine the window size of pooling layer and stride: The Pooling Window Size determines the size of the original data area covered by each operation. The stride size determines the distance of pooled window sliding on the feature map. The step size is usually 1 or 2, and when the step size is equal to the pool window size, there is no overlap between the pool windows.

Split the feature map and perform pooling operations: The input feature map is divided according to the pool window size and step size, and then each subregion is pooled (Max pooling or Average Pooling).

Generate the new pooled feature map: The outputs of all pooling operations are combined into a new feature map that is reduced in size relative to the original input feature map.

In general, pooling operation is an important down sampling method in convolutional neural networks, which down-samples local regions of feature graphs by specific rules. It is based on local correlation and invariance of features. In a feature map, adjacent regions often have similar features, so the amount of data can be reduced by aggregating these regions while retaining the main features [13,14].

Fully Connected Layer: The fully connected layer plays a classification or regression role in the CNN. It is usually located at the end of the network. Each neuron in the fully connected layer can perform a comprehensive analysis of the features extracted from the previous layer. The fully connected layer can then map the features of the input to the output space to enable classification, regression, or other predictive tasks on the data. The input to the previous layer is usually a multidimensional feature map that needs to be flattened to a one-dimensional vector before the layers are fully connected. Then, the connection and activation functions of the full connection layer integrate the local features extracted from the previous layer into the global features, thus facilitating subsequent tasks such as classification and regression [14].

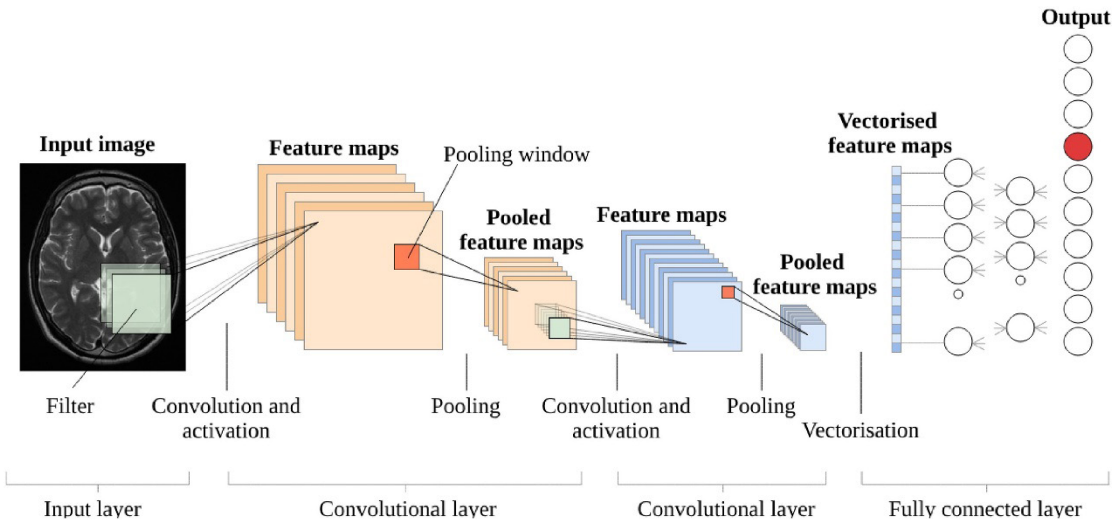

Fig. 1 Typical CNN process of MRI image

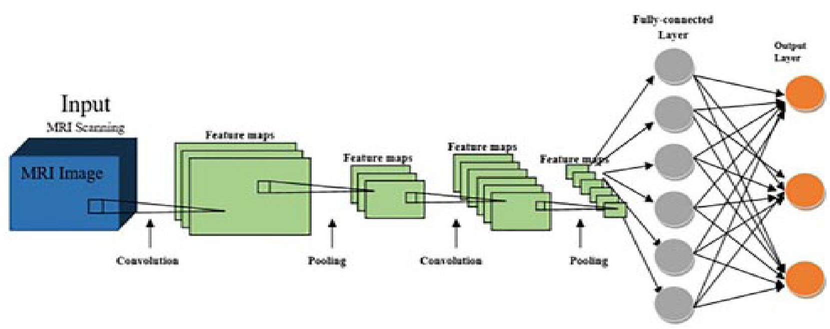

Fig. 2 Deep Learning process for disease diagnosis

Fig. 1 and Fig. 2 shows the flow of a typical convolutional neural network (CNN) for MRI image analysis. The first is the MRI scan, which is the source of the input data (the MRI image to be analysed). Next, the MRI images undergo a series of Convolution and Pooling operations. These operations are repeated several times to gradually extract the advanced features of the image. The extracted feature map then enters the Fully Connected Layer. The fully connected layer integrates and comprehensively analyses the features extracted above to learn the global relationship between the features. Finally, the fully connected Layer is connected to the Output Layer, and the output layer may perform operations such as classification (judging whether there is a lesion in the image), regression (predicting the size of the lesion) according to different tasks to obtain the final analysis result[15].

4. TYPICAL APPLICATION OF AI IN MRI

Breast Cancer Diagnosis: The breast cancer was and still is a major cause of cancer-related death among women worldwide. Detection and accurate diagnosis of breast cancer at an early stage can significantly reduce mortality. The use of AI-assisted magnetic resonance imaging in breast cancer diagnosis is gradually changing medical practice in this field. MRI can provide high-resolution images with good contrast to soft tissue. Deep learning CNN algorithms can automatically analyse the image features of breast MRI, such as shape, size, and edges, which can help detect early signs of breast cancer. In addition, ML classifiers for quantitative features related to nuclear shape, texture, and structure may also help predict the risk of early-stage positive breast cancer. Its accuracy rate can reach more than 80%. In general, although AI MRI has made significant progress in breast cancer diagnosis, there are still some challenges. The accuracy and prediction ability of AI diagnosis in clinical practice cannot meet the clinical application [16,17].

Skin disease diagnosis: Skin diseases are varied such as acne, skin cancer, skin rashes, etc. The early detection of skin diseases is important as a preventive measure. Although the application of AI-assisted magnetic resonance imaging in skin disease diagnosis is not as extensive as in other fields such as breast cancer, AI technology combined with other imaging methods has shown great potential in

ISSN 2959-6157

skin disease diagnosis. AI has excelled in the diagnosis of skin tumours such as melanoma and basal cell carcinoma. The different skin diseases can be classified using deep convolutional neural networks by collecting a large dataset of various skin disease MRI images and train the CNN model.

Brain tumour detection and diagnosis: The brain tumour is a kind of complicated and diverse diseases, its formation causes, symptoms, diagnosis and treatment methods have a certain complexity and diversity. Convolutional neural networks can detect brain tumours in MRI images, classify them (e.g., distinguish between benign and malignant tumours), and determine tumour boundaries.

Cardiovascular disease diagnosis: In heart MRI image analysis, AI can evaluate the structure and function of the heart. For example, by controlling parameters, the volume of the ventricle, the thickness of the myocardium and the movement of the myocardium are simulated. In addition, AI can also help identify plaque, stenosis and other lesions in the heart's blood vessels.

5. CONCLUSION

The current development trend of medical artificial intelligence is to integrate the image feature recognition and extraction of machine learning and deep learning into MRI image analysis. Convolutional neural networks and generative adversarial network models that can automatically extract complex features from MRI data. Some results have been achieved in automatic image segmentation, lesion detection and classification tasks. Although the deep learning algorithms like CNN are very effective at image segmentation and classification, traditional machine learning algorithms are still valuable for specific classification tasks, especially when dealing with smaller data sets or when machine performance is insufficient. However, there are still challenges to fully integrating AI into clinical practice, and these include the need for larger and broader data sets, as well as more clinical trials to verify the predictive accuracy and reliability of AI models. In conclusion, although AI has the potential to transform MRI-based diagnosis, continued research and development is needed to overcome existing limitations and ensure its widespread clinical application.

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