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Deep learning-based image classification of MRI brain image

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Abstract. This article reviews the latest research on MRI brain image classification techniques based on deep learning. Firstly, MRI brain image classification and traditional machine learning methods applied to MRI image classification were briefly introduced. Then, a review was conducted on existing MRI brain image classification methods based on deep learning. The article reviews past and recent related research and provides a detailed introduction to the application of deep learning methods in MRI brain image classification. This includes some traditional machine learning methods and research achievements in deep neural networks (DNN), convolutional neural networks (CNN), and transfer learning. The most commonly used deep learning architecture for image classification is CNN. Research has shown that deep learning methods have high accuracy and performance in MRI brain image classification and can automatically extract image features for effective classification. Therefore, deep learning methods provide doctors with more comprehensive information, help them make more accurate diagnoses and formulate treatment plans, and have broad prospects for application in MRI brain image classification. In the future, the further development of deep learning technology will achieve better auxiliary effects on diagnosis, treatment, and scientific research related to the brain.

Keywords: deep learning, machine learning, MRI brain image, image classification

1. Introduction

With the development of technology, medical imaging technology continues to improve. Medical imaging technology includes various technologies, such as X-ray and Magnetic resonance imaging (MRI), playing an increasingly important role in clinical diagnosis and treatment. Brain imaging is a key task with broad application prospects in medical imaging, which can help scientists and doctors gain a deeper understanding of brain structure, function, and activity through different imaging techniques, thereby promoting the development of disease diagnosis, treatment, and brain science research. Among various imaging techniques, MRI is the most commonly used technique for brain imaging. MRI is widely regarded as the main brain imaging technique for assisting in diagnosing and treating brain lesions such as brain tumors due to its non-invasive nature and ability to generate high-quality brain image [1].

However ,the traditional method in medical images field of manually selecting features relies on a large amount of professional knowledge and may result in some information in the image being ignored due to insufficient expression ability [2].

The concept of deep learning is an important research field in the field of machine learning. In recent years, deep learning has received increasing attention from relevant researchers. Applying deep learning method can find the internal structure of the data and discover the true relationship between data [3]. This demonstrates its ability to sensitively and effectively find hidden information and features in a large amount of data. Deep learning algorithms have important and widespread applications in audio recognition, image and video recognition, information retrieval, and related fields [3]. The development of deep learning also contributes to the recognition, classification, and quantification of patterns in medical images [4]. In medical image processing, the application of deep learning can improve the efficiency and accuracy of diagnosis, and fully express important information in medical images. Due to the ability of deep learning to accurately analyze a large amount of data, compared to manual work, this approach can extract more information from images and provide new developments in the medical field. Introducing deep learning into MRI brain imaging classification can also provide doctors with more comprehensive information, thereby assisting them in making more accurate diagnoses and providing treatment plans [1]. Therefore, the research on MRI brain imaging classification based on deep learning is very valuable and has received widespread attention.

This article reviews and summarizes the recent MRI brain image classification techniques based on deep learning. Firstly, a brief introduction was given to the MRI brain image classification and traditional machine learning methods applied to MRI image classification. Then, existing MRI brain image classification methods based on deep learning were reviewed.

2. Traditional machine learning methods of MRI brain image classification

In MRI medical imaging, due to various influences on the imaging process, such as tissue movement and artifacts caused by metal implants in the body, medical images inevitably have characteristics such as blurred edges of various tissues and uneven regional grayscale [5]. These will bring many difficulties to correctly classifying MRI brain imaging categories. In traditional machine learning, many different methods are applied to solve the classification problem of brain MRI images. Feature extraction and feature classification are the two main parts of machine learning for classifying MRI images. In addition to the feature extraction section, where researchers choose the feature extraction method for MRI images, different methods will also construct different classifiers. The algorithms or models they use to classify input data are different.

Support Vector Machine (SVM) is a classic classifier performing well in sample, high-dimensional, and nonlinear sample learning [5]. SVM has also been proposed in imaging to classify MRI images. In a 2013 study of Rosy Kumari, SVM was considered to have better accuracy and performance than other classifiers and was therefore selected for classification of MRI brain images [6]. Researchers used SVM to classify normal and abnormal brain images, as shown in Figures 1 and 2 [6]. This study used the Gray-Level Co-occurrence Matrix (GLCM) method to extract statistical texture features. This method can capture texture, structure, and spatial features by statistically analyzing the relationships between each pair of pixels in the image. SVM is a supervised learning based binary classifier that can construct a hyperplane in a high-dimensional feature space that can be used for classification. The classification stage of the study is divided into training and testing stages. During the training phase, brain image images were used to separate the feature attributes of image features, and separate and unique descriptions were provided for each classified category. In the testing phase, these feature space partitions created during the training phase are used to classify the image features of new brain images. The test results of this study indicate that the SVM method for MRI image classification has relatively high sensitivity, specificity, accuracy, and efficiency. By using the most effective kernel function, the accuracy of classifying normal and abnormal can reach 98.45% [6].

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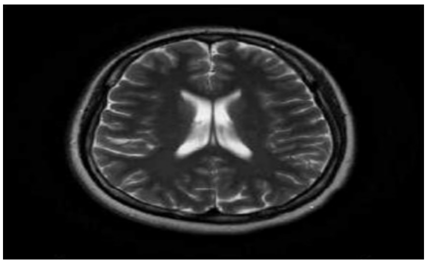

Figure 1. Normal MRI brain image [6].

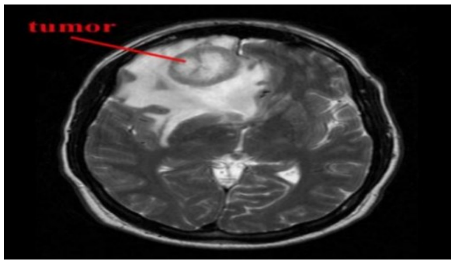

Figure 2. Abnormal MRI brain image [6].

In an intelligent classification study of Alzheimer's disease, researchers such as Zheng Yao used multiple machine learning classifiers. This includes using SVM based on paired classification to achieve intelligent diagnosis of AD. In these studies, researchers gradually optimized from a simple SVM binary problem to a five class problem, achieving an accuracy of 0.71 in the diagnosis of Alzheimer's disease [7].

Random forest is a combination classifier in machine learning, which can also achieve high accuracy in classification. In a previous Zhan Shu et al. study, random forests were used for MRI brain image classification [5]. In terms of feature extraction for brain MRI images, this study takes texture, grayscale, histogram features, Otsu threshold, and shape features [5]. The diversified feature extraction in this study can enrich the expression of image features. The core idea of random forests is to integrate multiple weak classifiers to achieve accurate classification results. After multiple experiments, the optimal coefficient of the model was obtained. The accuracy achieved with this coefficient is 0.941 [5].

In the study by Zheng Yao et al., the random forest method was also used for MRI brain image classification to diagnose Alzheimer's disease, but the accuracy obtained was 0.69, slightly lower than the SVM method [7].

However, researchers still raised a problem: In the training stage of machine learning, the prior knowledge of class labels of some pixels in the image needs to be classified first, which hinders the practical application of the random forest algorithm [5]. This issue has also become a follow-up research direction, including the researchers of this study [5]. Nowadays, this focal problem at that time can be solved through the application of deep learning. Nowadays, this focus issue can be solved through the application and development of deep learning technology, as deep learning has a certain degree of automatic feature extraction ability.

3. Deep learning based image classification of MRI brain image

Based on machine learning, deep learning is a special machine learning method that mimics the neural network structure of the human brain and learns and processes data through multi-level neural networks. Compared to traditional machine learning, deep learning uses deeper neural networks that learn complex relationships between data, which enables it to demonstrate stronger capabilities when dealing with complex data and problems. To some extent, deep learning can automatically extract features from data or images, and designing feature extraction can help further improve the performance of deep learning models. In recent years, more and more researchers have utilized the ability of deep learning to simulate more complex nonlinear relationships and its excellent performance, creating the current best solutions for many problems in medical image analysis applications [8].

There are different architectures for deep learning. DNN is widely used for classification or regression [8]. This method has also been widely applied in various fields and has achieved success in recent years. In the study by Heba Mohsen et al., deep neural networks were applied to classify brain tumors in brain MRIs [8]. In this study, certain feature extraction methods were still used. The research aims to apply deep learning techniques to classify brain MRIs and distinguish between normal brain and certain types of brain tumors, such as metastatic bronchial cancer tumors, glioblastoma, and sarcoma, and measure classification performance based on the obtained results. The dataset used in this research contains 66 real human brain MRIs, including normal and abnormal images. The three types of brain tumors mentioned above appear in abnormal images. In the research process, the fuzzy C-means image segmentation technique was used to divide the brain MRI image into five parts: gray matter, white matter, cerebrospinal fluid, and skull and tumor tissue. The segmented tumor image is used for subsequent classification. Afterwards, due to the advantage of discrete wavelet transform in extracting the most relevant features in different directions and scales [8], this method was used for feature extraction of brain tumor images. This study uses deep neural network (DNN) to classify the generated feature vectors in the classification step. Using a 7-layer hidden layer structure of DNN and 7-fold cross validation technology for construction and training, its performance was evaluated on multiple performance indicators such as average classification rate, recall rate, accuracy, F-measurement value, and area under ROC curve. The results indicate that DNN classifiers perform well in all performance metrics compared to other classifiers. The accuracy reaches 96.97%, higher than traditional classifiers [8]. The results of this study emphasize the excellent performance and potential of DNN and deep learning in classification tasks.

CNN are a deep learning model widely used in medical image processing, and are most widely used in the classification of MRI brain images. In the study of Wadhah Ayadi et al., a new deep convolutional neural network (CNN) model was proposed for multi class classification of MRI brain tumors [9]. In this study, manual feature extraction was no longer necessary and automation was achieved. The general architecture of the proposed sequential model is shown in the figure 3.

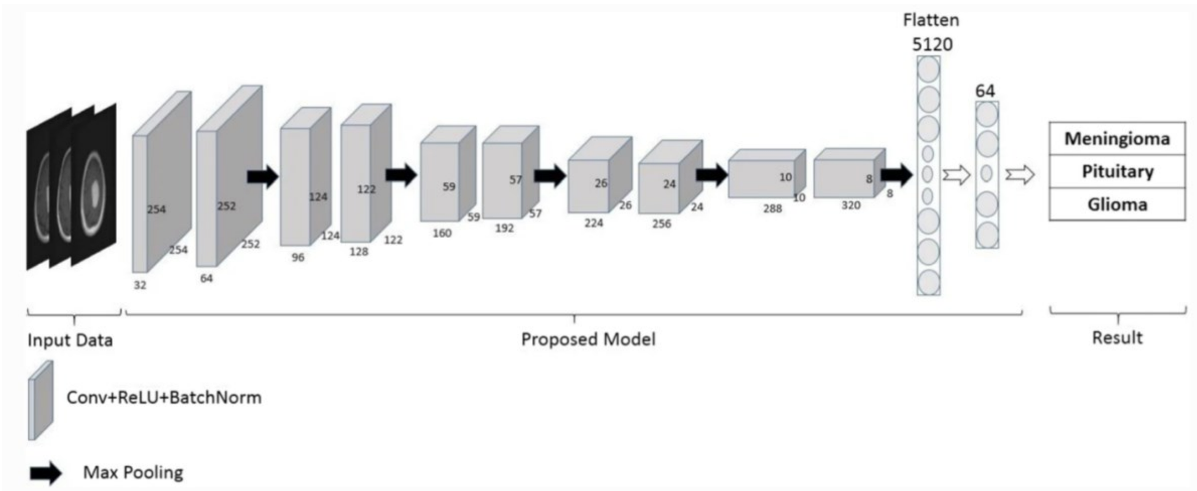

Figure 3. General architecture of sequential models [9].

The model consists of a 10 convolutional layer to extract features from MRI images, as shown in Figure 3 [9]. Because the complexity of CNN models increases with the increase of input size, researchers propose that reducing size can be used to minimize time complexity. The researchers used three common datasets to validate the performance of the model. The research results show that the model achieved the highest accuracy in MRI brain tumor classification. Compared to previous technologies, this model overcomes the difficulty of manually extracting features and achieves automation by using minimal preprocessing. The experimental results indicate that the model still has high effectiveness even in small datasets. The researcher's paper also mentioned that the model's structural selection and hyperparameter adjustment are effective for processing MRI images and obtaining more accurate results. In addition, this model has broad application prospects and can be used for other medical image classification, with strong application robustness.

Transfer learning is also effective in deep learning MRI brain image classification. In a study by Muhammad Fayaz et al., the CNN architecture was pre-trained on a large labeled dataset (ImageNet) using transfer learning to automatically analyze brain MRI images in Alzheimer's disease prognosis

[10]. In this study, researchers used a CNN architecture called AlexNet, which was trained on the ImageNet dataset. Through transfer learning, researchers transferred low-level features from the AlexNet model to the Alzheimer's disease classification task. This application of transfer learning can accelerate the learning speed of the model. In transfer learning, pre-training is conducted on a large dataset, and then the learned feature knowledge is transferred to the target task to improve the classification ability of the target task data. This step played a crucial role in this study. It enables CNN models trained on large datasets to exhibit higher accuracy and performance in medical image classification tasks. Enable researchers to transfer knowledge learned from natural images to medical image classification, thereby improving the accuracy of detection and analysis of Alzheimer's disease. After applying transfer learning, researchers used features learned from the ImageNet dataset for multi class classification of Alzheimer's disease, including subjects in normal, mild dementia, and moderate dementia stages. The classification results indicate that the system performs best in multi class classification of unsegmented images, with an accuracy of 92.8%. This method has achieved high accuracy in classifying test subjects as having Alzheimer's disease or not. This study has achieved significant results in the classification of Alzheimer's disease using MRI brain imaging, achieving an efficient automated system and providing an effective and accurate method for the classification and prognosis analysis of Alzheimer's disease.

A fundamental drawback of CNN is its lack of interpretability for its output [11], which is necessary to improve the model's reliability. In Shakila's study, an MRI dataset was used to train a 3D-CNN model to distinguish between cognitively normal individuals and Alzheimer's disease (AD) patients [11]. This study combined genetic algorithms and interpretability methods to extract important brain regions that significantly impact AD diagnosis. The study first used genetic algorithms and backpropagation-based interpretability methods to generate an occlusion map mask, and then improved it through an iterative process. Finally, the study obtained a brain mask from an AD patient composed of important brain regions. To verify the effectiveness of these extracted regions, the study compared them with expert research in the field, and the results showed that the model achieved an acceptable accuracy of 87% in 5-fold cross validation. Afterwards, the study used an unobstructed dataset with 96 different brain regions, trained a 3D-CNN model with an accuracy of 96%, and used it in the genetic algorithm stage to generate appropriate brain masks. Finally, using the interpretability method based on backpropagation, the study achieved a validation accuracy of 93% in 29 brain regions. This study extracted important brain regions of AD patients by combining genetic algorithms and interpretability methods, and demonstrated the effectiveness of this method. By improving the interpretability and accuracy of the model, research has contributed to the automatic diagnosis of AD.

Hossein Mehnatkesh et al. proposed an improved ant colony algorithm (IACO) to optimize the hyperparameters of classification algorithms and chose to use ResNet architecture [12]. To improve the accuracy of brain tumor classification, researchers first preprocess the images and select the most suitable pre-training model for the dataset. The researchers compared seven pre training structures and seven optimization methods, and selected ResNet and IACO, which had the best performance on the dataset, as the final models and optimization algorithms. Compared with other methods, the research results show that the proposed method has high performance and reliability. Finally, the model with the best hyperparameters was obtained. A new evolutionary strategy was introduced to solve the hyperparameter optimization problem of deep learning algorithms, and an improved ant colony algorithm (IACO) was proposed based on the most effective ant colony algorithm (CAO) among the original meta heuristic algorithms to improve the convergence speed and accuracy of the algorithm. This method has been experimentally validated and achieved high accuracy in brain tumor classification, reaching an accuracy of 99.02%, the highest among the seven meta heuristic algorithms. However, implementing this method is relatively time-consuming and requires further development of parallel algorithms to improve efficiency. This study provides a fully automated brain MRI image classification system that utilizes deep learning and evolutionary algorithms to obtain the optimal hyperparameters and model structure, which has good reliability in brain tumor classification of MRI images.

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4. Conclusion

In conclusion, the MRI brain image classification method based on deep learning has important application value and broad prospects in the medical field. Compared to traditional machine learning methods, deep learning utilizes deeper neural network structures to learn complex data relationships, effectively extracting features automatically and achieving significant results in Brain MRI Image Classification. In MRI brain image classification, researchers have applied different deep learning models and methods, such as CNN, DNN, and transfer learning, to improve the accuracy and performance of classification. DNN have shown promise in their ability to automatically extract intricate features from MRI images, reducing the burden of manual feature engineering. It can be found that CNN is the most commonly used model architecture for computer vision tasks such as image classification. It has become the workhorse for MRI brain image classification, exhibiting remarkable accuracy and performance. Transfer learning has also played a pivotal role, allowing the transfer of knowledge learned from large datasets to enhance the classification of brain images. At now, deep learning-based MRI brain image classification has already made significant strides in improving diagnosis and treatment planning. It has the potential to revolutionize the field of medical imaging by providing more accurate, efficient, and interpretable tools. Looking ahead, the future of MRI brain image classification based on deep learning holds tremendous promise. As technology continues to advance, the future of MRI brain image classification is bright, promising better outcomes for patients and further advancements in brain science research.

References

[1] Jiang Z, Lyu X, Zhang J, Zhang Q and Wei X 2020 *J. Journal of Image and Graphics* **25(2)** 215-228
[2] Song J, Xiao L, Lian Z, Cai Z, Jiang G 2020 *J. Journal of Software* **32(5)** 1427-1460.
[3] Liu J, Liu Y, Luo X 2014 *J. Application Research of Computers/Jisuanji Yingyong Yanjiu* **31** 1921-1930
[4] Shen D, Wu G, Suk H. 2017 *J. Annual review of biomedical engineering* **19** 221-248
[5] Zhan S, Yao Y, Gao H 2013 *J. Journal of Electronic Measurement and Instrumentation* **27(11)** 1067-1072
[6] Kumari R 2013 *J. Int. J. Eng. Res. Appl* **3(4)** 1686-1690.
[7] Zheng Y, Yang T, Zhou Z 2023 *J. Modeling and Simulation* **12** 1321-1330
[8] Mohsen H, El-Dahshan E S A, El-Horbaty E S M, et al 2018 J. Future Computing and Informatics Journal **3(1)** 68-71.
[9] Ayadi W, Elhamzi W, Charfi I, et al 2021 *J. Neural processing letters* **53** 671-700
[10] Fayaz, M. Torokeldiev, N. Turdumamatov, S. Qureshi, M.S. Qureshi, M.B. Gwak 2021 *J. Sensors* **21(22)** 7480
[11] Shojaei S, Abadeh M, Momeni Z 2023 *J. Expert Systems with Applications* **220** 119709
[12] Mehnatkesh H, Jalali S, Khosravi A, et al 2023 *J. Expert Systems with Applications* **213** 119087