Advances and Challenges of Machine Learning in Brain Medical Imaging Data Analysis

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Abstract: In recent years, machine learning has become a critical method for medical imaging data analysis and has solved many problems in medical imaging. This study focuses on brain medical imaging data analysis, and summarizes the advances and challenges of machine learning in this field. The methods range from traditional machine learning models to emerging machine learning models. These approaches have been improved and solved many problems, such as image quality problem, generalization problem and so on. However, there are still many challenges for machine learning in the field of brain medical imaging, including data annotation and model training problem, non-interpretability of the model and Cross-domain and cross-site data integration problem. These challenges not only affect the depth of research, but also hinder the clinical translation of new technologies. Therefore, how to overcome these obstacles has become the key to promote the further development of this field. This study also proposes some possible solutions to these challenges that could be further explored in the future.

1 INTRODUCTION

Nowadays, brain medical imaging is becoming a significant field because of the increasing number and complexity of brain disorders. And the appearance of machine learning has greatly contributed to the development of this field. As noted by Shrivastava et al. in recent studies, including preprocessing, segmentation, feature extraction, and classification, are helpful to the development of brain medical imaging analysis. However, new brain diseases keep coming up over time, and the existing machine learning methods also have some challenges to analysis the brain medical imaging specifically and accurately.

This review aims to summarize the recent advances of machine learning in brain medical imaging and also the challenges faced by this field. The advances represent the progress of machine learning in brain medical imaging over the years, including the improvement of old models and the proposal of new models. The challenges represent that there is still room for progress in machine learning in this field, and there are still areas that need to be improved and strengthened. This study has sorted out these advances and challenges, which also has great implications for future research and point the way.

The rest of this paper is organised as follows: Section 2,3,4 reviews the advancements and discusses the challenges of machine learning in brain medical imaging analysis, Section 5 summarizes the advances and challenges and also has a discussion of future research trends.

2 EFFECTS OF MACHINE LEARNING IN BRAIN MEDICAL IMAGING

This section will introduce the effects of machine learning in the processing tasks of medical images, which mainly focused on technical aspects.

2.1 Basic Overview

Machine learning and even the deep learning have a mass of effects in the medical image of the brain, such as image segmentation, classification, and reconstruction. Fully convolutional networks (FCNs) are being found useful. Compared with convolutional

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neural networks (CNNs), FCNs return to full-resolution images, which is better at biomedical image segmentation.

Previous research by Barragán-Montero and colleagues highlighted a new concept, adversarial learning, means that the models are trained in the presence of adverse samples. Generative adversarial networks (GANs) have been improved step by step and is widely used in the realm of medical imaging. As shown by Barragán-Montero et al., GANs are mostly used in multi-modality image translation and data augmentation in synthetic picture synthesis. There are also many other architectures such as Support Vector Machine (SVM), Long Short-Term Memory (LSTM), and U-NET (U-Net: Convolutional Networks for Biomedical Image Segmentation) etc., have also been applied in medical imaging field.

2.2 Deep Learning for MRI Reconstruction

As noted by Yadav et al. in recent studies, the use of medical imaging is helpful for the recognition of brain tumors, which could strengthen patient care and lessen suffering. This is because magnetic resonance imaging (MRI) uses no ionizing radiation. As shown by Yadav et al., MRI could display many tissues in high resolution and great contrast.

A study has shown that Hue, Saturation, Value (HSV) Histogram and Gabor Wavelet could improve the accuracy of the MRI imaging analysis. As shown in Figure 1, the procedure includes preprocessing, segmentation and clustering, and others.

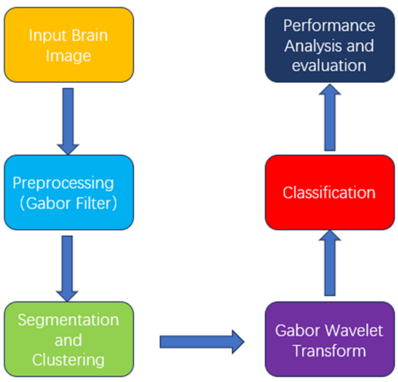

Figure 1: The Proposed Work Flow (Yadav, D. C., Sharma, N., & Kudari, J. M., 2023)

A technology proposed by another research has also contributed to the improvement of MRI image technology. Previous research by Zhao and colleagues highlighted that three schemes make up the technology: U-Net, modified Akima segmented cubic Hermite interpolation (MASCHI) scheme, and parallel semi-connected back-propagation neural network (SJ-BPNN) scheme, which significantly increased the image resolution.

2.3 Innovations in Deep Learning Architecture

Based on the attention mechanism, a study by Yang and colleagues has presented a multi-offset reconstruction method (AMO-CEST), which can not only accelerate Chemical Exchange Saturation Transfer Magnetic Resonance Imaging (CEST-MRI) acquisition, but also maintain suitable image quality. This technology improves the quality of MRI image technology to some extent.

3 MACHINE LEARNING IN DISEASES DIAGNOSIS

This section will introduce the practical clinical application of machine learning, especially the specific tasks in the diagnosis of brain diseases. This part mainly takes brain tumor disease as an example.

3.1 Deep Learning in Brain Tumor Detection

A study by Tang and colleagues has proposed a methodology based on Residual Network with 18 layers (ResNet18) deep learning architecture. In the study, the authors evaluate neural network by testing dataset and found that the accuracy, specificity, and precision are better than previous models in deep learning. This result indicates that the ResNet18 model can correctly classify the most of the images, identify healthy brain images and avoid false positives. One of the reasons is that the ResNet18 model is trained on a large dataset and then use transfer learning to fine-tuned on a smaller dataset (Tang et al., 2023). Additionally, ResNet18 model have residual blocks, which are helpful to solve gradient degradation problem. As a result, the ResNet18 is crucial for the classification of brain diseases, and then the analysis of medical imaging.

Another research by Zubair Rahman and colleagues has presented a novel Artificial Intelligence-driven (AI-driven) methodology based on Efficient Neural Network B2 (EfficientNetB2) deep learning architecture. And the architecture diagram of the model is shown in Figure 2. The method could deal with a mass of problems that brain tumor detection faced, such as noise and changes in image quality, which is helpful for the detection of brain tumors from MRI images (Zubair Rahman etal., 2024). The study was tested on a mass of publicly available data sets and show high accuracy. This indicates that AI-driven tumor detection models are not only innovative in theory, but also have wide application potential in practice.

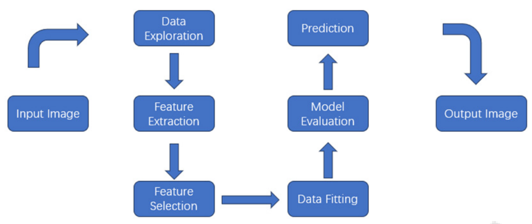

Figure 2: The Architectural Diagram of Model (Zubair Rahman etal., 2024)

3.2 Deep Learning in Brain Tumor Segmentation

As noted by Dong et al. in recent studies, good image segmentation methods are crucial for the 3D geometric modelling while diagnosing and operating. To divide primary brain tumors from normal brain tissues, a study proposed a deep learning method based on a 3D U-net with deep supervision and multi-scale in continuous experiments and innovations. 3D U-net is used to process 3D medical image data, making full use of spatial information in volume data and preserving detailed features through jump connections. The integration of deep supervision, that is, supervised learning at multiple layers of the network, not just at the final output layer, ensures that multiple layers can be effectively trained. Additionally, the multi-scale inputs enable the model to handle tumor regions of different sizes, thus improving the model's ability to adjust to intricate tumor form.The algorithm performs exceptionally well in terms of segmentation accuracy and processing speed, according to experimental results. The model is helpful for the clinical diagnosis.

Research by Taleb and colleagues has developed five 3D self-supervised methods: 3D Contrastive Predictive Coding, 3D Rotation prediction, 3D Jigsaw puzzles, Relative 3D patch location, and 3D Exemplar networks. Based on experimental results, 3D Self-supervised model performs better than 2D models, in particular, significantly outperforms models trained from scratch when using fewer training samples. With 3D self-supervised pre-training, the model is able to learn richer contextual information, which is crucial for medical image segmentation. And 3D Self-supervised model has the ability to isolate tumors from MRIs accurately. Additionally, 3D task for pre-training demonstrates good cross-domain generalization, especially with less labelled data. Future expansion could extend this 3D pre-training method to other 3D medical imaging areas such as Computed Tomography (CT) scans, Positron Emission Tomography (PET), etc. As a result, self-supervised pretraining is particularly suitable for scenarios where medical image data is abundant but annotation is scarce.

4 MACHINE LEARNING CHALLENGES IN BRAIN IMAGING

This section will list some of the challenges of machine learning in brain image data.

4.1 Data Annotation & Training Issues

As shown by Taleb et al., the scarcity of data and annotations is a major challenge in model development and application in the medical imaging field. Acquiring medical image data is complex, which require high-cost medical equipment and the operation of professional personnel. Labelling of these data consumes a mass of time and requires the domain experts to participate. The accuracy of labelling directly affects the performance of the model. It is possible that transfer learning can be used to reduce the reliance on large-scale labelled medical data.

As noted by Liu et al. in recent studies, class imbalances are also challenges of medical image analysis. Proposing new loss functions has the potential to solve this problem.

Additionally, as shown by Li et al., although the machine learning-based brain image analysis methods proposed by this study have good performance, it is still difficult to find a balance between efficiency and accuracy. The computational complexity could be reduced and the inference speed improved while maintaining model performance through model compression technology.

4.2 Model Non-Interpretability

As shown by Eder et al., the internal decision-making process of machine learning cannot be explained at all when working with complex data, which makes it difficult for healthcare professionals to trust and verify Artificial Intelligence (AI) results.

Black box algorithms, for example, whose opacity leads to a host of problems, including potential bias, attribution of responsibility, patient autonomy, and erosion of trust (Durán, J. M., & Jongsma, K. R., 2021). Computer reliability theory supports the reliability of algorithms without necessarily requiring their transparency. However, it is crucial to note that ethical concerns remain important. The doctors must take the best care based on trust.

4.3 Cross-Domain & Cross-Site Integration

When data is collected at multiple sites, differences between the data can interfere with model training due to different equipment, experimental conditions, and participant characteristics (Bostami, B., Espinoza, F. A., van der Horn, H. J., Van Der Naalt, J., Calhoun, V. D., & Vergara, V. M.,2022). The site effect can reduce the generalization ability of the model. Harmonization may solve this problem to some extent, which can standardize the data and improve the reliability of the model.

Datasets from different domains are difficult to integrate because they differ in collection methods, labelling standards, and formats (Said, A., Bayrak, R., Derr, T., Shabbir, M., Moyer, D., Chang, C., & Koutsoukos, X., 2023). And data preprocessing requirements may be different from domain to domain. It is possible to solve this problem by unifying data formats or creating flexible preprocessing frameworks.

5 CONCLUSIONS

This study has discussed the advances in brain medical imaging and a mass of innovative methods and models. Although significant advances have made in the field of brain medical imaging based on machine learning, the scarcity of data and annotations, non-interpretability of the model and the problem of cross-domain and cross-site data integration limit the broader application of medical learning in this area. Future research should develop more generalizable models and combine with interpretable technology. By solving these problems, brain medical imaging analysis will make more contributions to personalized medical and precision medical.

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