HYBRID DEEP LEARNING ENHANCES MRI BRAIN TISSUE SEGMENTATION AND TUMOR LOCALIZATION

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Abstract: Using Hybrid Deep Learning, researchers in the scientific community have created a novel method for analyzing brain images taken as part of the Human Connectome Project. For the purpose of precise volumetric segmentation of brain tumors and tissues from MR images, the Aligned Cross-Modality Interaction Network (ACMINet) and APRNet have been presented as potential solutions. While APRNet delivers state-of-the-art outcomes on benchmark datasets, ACMINet works to improve multi-modal features. DDSeg is a deep learning approach that improves accuracy and predicts tissue segmentation without the need for anatomical data and inter-modality registration. This is accomplished by learning tissue segmentation using high-quality imaging data that is obtained from the Human Connectome Project.

Keywords: MRI Images, Image fusion, Brain tumor segmentation, Tumor Localization, health care, HCP database, ACMINet, APRNet, DDSeg, CNN, RNN, Deep Learning, Deep Neural Networks. Neurological disorders & diagnosis

DOI: 10.48047/ecb/2023.12.8.737

INTRODUCTION:

It is possible that deep learning will have a considerable influence on medical picture classification and segmentation, paving the way for the automation of non-invasive imaging-based diagnosis. The use of recent advancements in medical image processing by computer-assisted brain tumor diagnostics has opened the door to potentially fruitful research efforts in deep learning areas. This may pave the way for the creation of automated diagnostic systems that are reliable for use by medical professionals.

For the analysis of dMRI data, a deep learning brain tissue segmentation algorithm has been developed. A CNN model is trained by using MK-Curve-based DKI features as well as a newly developed enhanced target loss function. This approach avoids the need for inter-modality registration while producing results that are equivalent to those of anatomical MRI-based tissue segmentation. It also works well with dMRI data that has lower spatial and angular resolutions, and it outperforms other approaches that are considered to be state-of-the-art in both quantitative and visual comparisons.

A Transformer-CNN hybrid deep learning architecture for brain tissue segmentation has shown superior performance compared to previous CNN implementations. It generalizes well across datasets and remains reliable between paired test-retest scans, making it a useful toolkit. The methodological utility of a Vision Transformer improves the Unet architecture for brain tissue segmentation.

Medical imaging

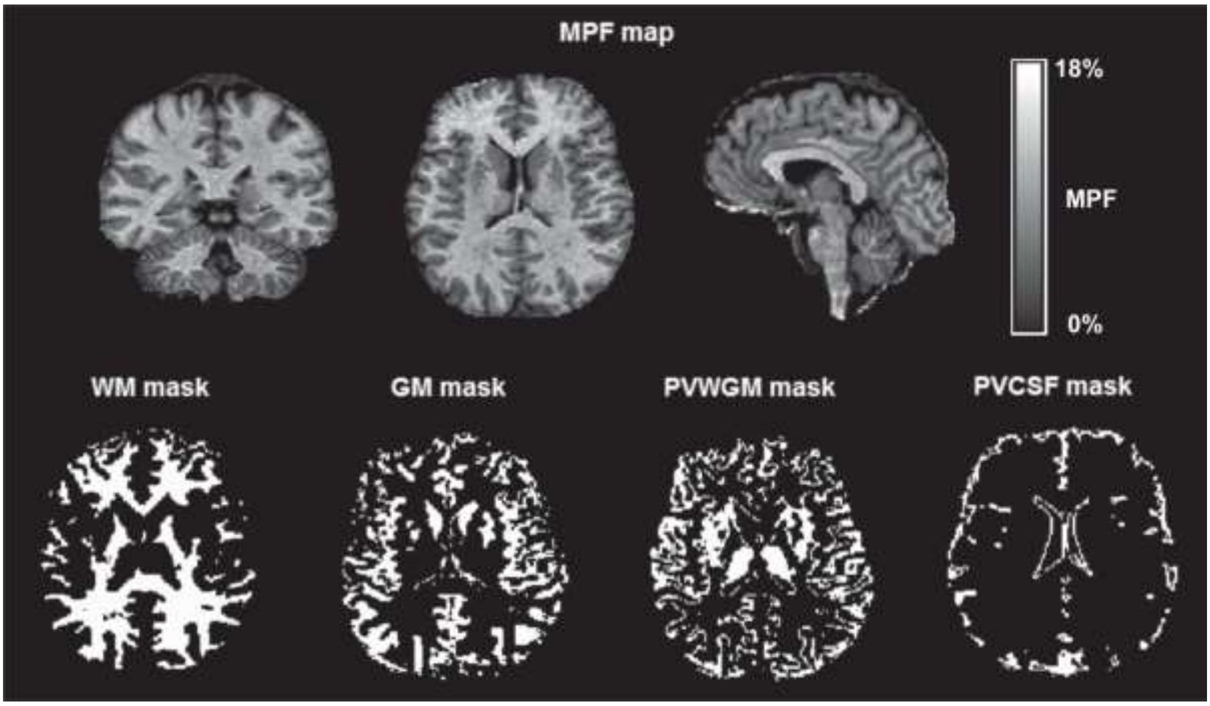


Figure 1. Brain tissue segmentation masks obtained from MRI images

3D CNN models require significant computational power for efficient training. The model used full-resolution MRI inputs but faced memory constraints. A larger batch size could have improved performance. Additionally, TABS could be improved by increasing sample size, as it could account for variations in MRI image characteristics not captured in the datasets studied.

In this paper makes the following way:

- Deep learning is crucial in medical image segmentation, particularly in brain tissue and tumor analysis using MRI data.
- It improves accuracy compared to manual methods, enabling accurate brain examination, diagnosis, and classification.
- Hybrid deep learning, combining CNN and RNN, differentiates brain parts, improves tumor diagnosis, and provides brain care.

LITERATURE SURVEY:

MRI scans are used by researchers and medical professionals to get a better understanding of brain disorders and to assist patients, but it may be difficult to convey the information contained in these pictures. Image identification and the detection of patterns in brain pictures may be improved using a technique known as hybrid deep learning, which combines two types of neural networks: convolutional neural networks (CNN) and recurrent neural networks (RNN). This results in improved cooperation, the identification of brain sections such as the white stuff, the grey stuff, and the watery portion, the detection of cancers, improvements in diagnosis and therapy, and, eventually, an improvement in brain health.

METHODS:

The research will involve the following steps:

Dataset Collection: Gather a large dataset of MRI images containing brain tissue and labeled tumor localization. The dataset should cover a diverse range of patients with different conditions and lesion characteristics.

Preprocessing: Preprocess the MRI images to enhance their quality and remove noise. This may involve intensity normalization, bias field correction, and registration to a common anatomical template.

Network Architecture: Design a deep neural network architecture specifically tailored for the segmentation task. The architecture should incorporate optimization techniques, such as incorporating regularization terms, to improve the network's ability to capture fine details and handle class imbalance.

Training: Train the deep neural network using the collected dataset. This involves feeding the MRI images into the network and optimizing the network parameters to minimize the segmentation error. The optimization process may involve gradient descent-based methods or more advanced optimization algorithms.

Evaluation: Evaluate the trained model's performance using appropriate evaluation metrics such as Dice similarity coefficient, Jaccard index, sensitivity, specificity, and accuracy. Compare the results with existing segmentation methods and assess the model's robustness and generalization ability.

Fine-tuning and Optimization: Fine-tune the model based on the evaluation results and address any limitations or issues identified during the evaluation phase. Optimize the hyperparameters and network architecture to improve the segmentation performance.

Validation: Validate the optimized model using an independent dataset to assess its generalization ability and reliability. This step helps to ensure that the developed model performs well on unseen data and can be applicable in real-world clinical settings.

Comparison and Analysis: Compare the performance of the optimization-based hybrid deep neural network model with existing segmentation methods, such as traditional machine learning techniques or other deep learning approaches. Analyze the strengths, weaknesses, and limitations of the proposed method and discuss potential future research directions.

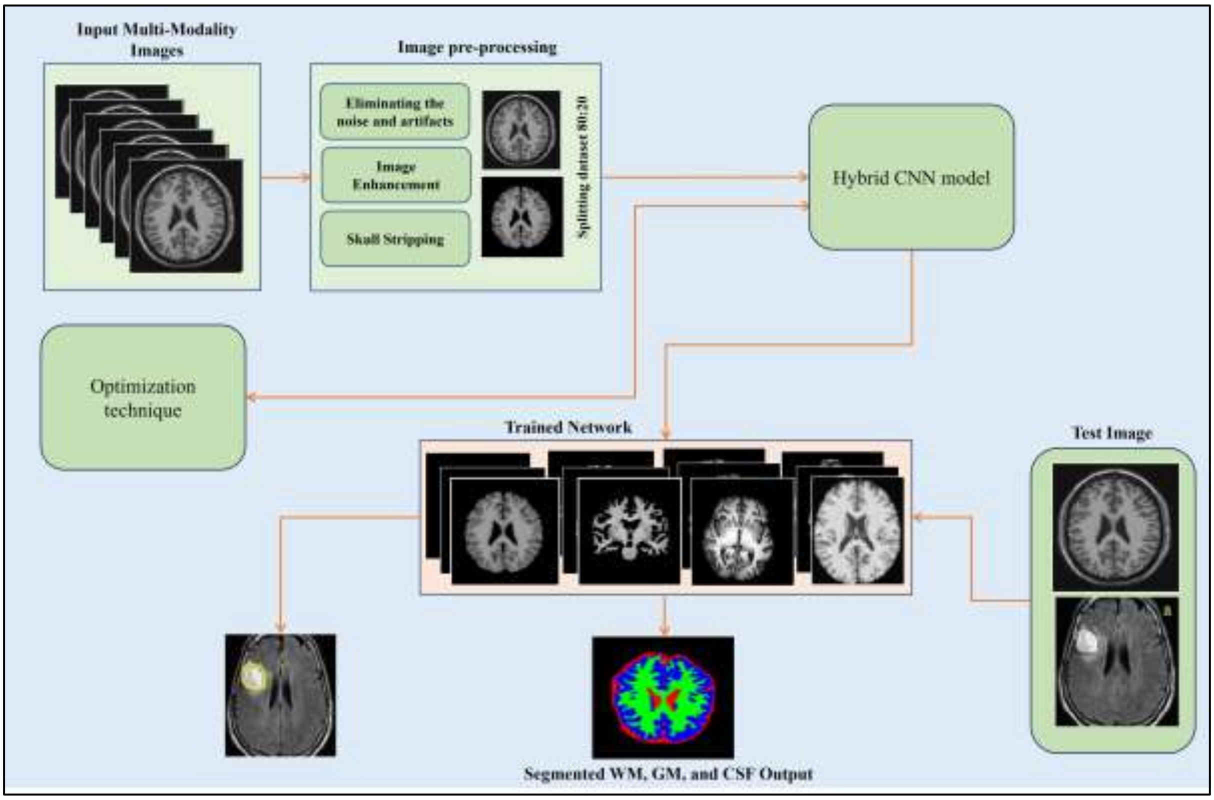


Figure 2. The Overall architecture of the proposed model

The proposed method includes 3 main steps:

(a) Extracting a tissue feature descriptor from DKI and MK-Curve-based measures

(b) Training a CNN model for tissue segmentation and

(c) Predicting subject-specific tissue segmentation from new dMRI data.

(a) Extracting a tissue feature descriptor from DKI and MK-Curve-based measures: Study uses DKI model fit and MK-Curve for enhanced white matter alterations in psychosis patients.

(b) Training a CNN model for tissue segmentation: CNNs trained models for segmenting WM, GM, and CSF from dMRI descriptors using convolution, pooling, and fully connected layers. There were two main CNN design choices: 1) choice of CNN architecture, and 2) design of loss function.

(c) Predicting subject-specific tissue segmentation from new dMRI data: To perform tissue segmentation on new subjects, a trained CNN model was applied to dMRI data, extracting tissue feature descriptors, and generating segmentation probability maps. The 3D map was computed from these probabilistic maps.

Research Motivation:

Research aims to improve segmentation accuracy in medical image analysis using optimization-based hybrid deep neural networks for brain tissue and tumor localization segmentation in MRI images.

1. Clinical Importance: Research develops optimization-based deep neural network for improved MRI segmentation accuracy.
2. Limitations of Existing Methods: Traditional segmentation methods for brain tissue and tumor localization face limitations; deep learning techniques address these challenges.
3. Integration of Optimization Techniques: Optimization techniques improve deep neural networks' segmentation accuracy, capturing complex brain tissue and tumor patterns.
4. Clinical Workflow Efficiency: Deep neural network segments brain tissue in MRI images, reducing manual labor.
5. Advancements in Deep Learning: Deep learning advances focus on brain tissue segmentation for clinical applications.

Objectives:

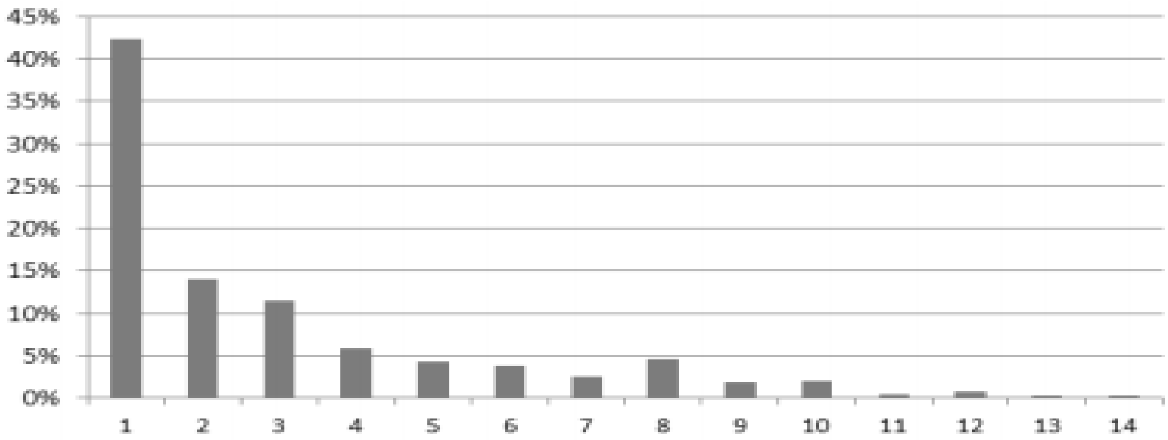
Main objectives of this paper are:

1. Create optimization-based deep neural network model for accurate brain tissue segmentation and tumor localization.
2. Assess model's clinical applicability and potential early neurological disorder detection.
3. Address class imbalance challenges in segmentation, focusing on rare tumor localization.

Expected Outcomes:

1. Hybrid deep neural network model aims for improved segmentation accuracy, robustness, and tumor segmentation across diverse patient populations.
2. Optimization-based approach improves segmentation model efficiency, enabling feasible clinical applications and superior performance compared to traditional methods.

Users	**Full Text Queries**	**Of Faceted Queries**	**Last Posted Contents**	**Featured Contents**	**Popular Contents**
Simple Registered	323	24	4	22	17
Registered As Partners	1094	21	27	19	9
Anonymous	2634	147	234	302	213
Total	4051	192	265	343	239
Clicks after query	1564	200	318	2799	231



Limitations/ De-limitations:

Limitations:

1. Availability and Quality of Data: Optimization-based deep neural network model performance depends on MRI dataset availability.
2. Computation and Resource Requirements: Deep neural networks require significant computational resources, impacting training time and implementation.
3. Generalization to Different Scanners and Acquisition Protocols: Applying to various scanners and acquisition protocols.
4. Improved Interpretability of Results.

De-limitations:

1. Optimization-Based Deep Neural Network Approach: Research explores optimization-based deep neural network for segmentation accuracy.
2. Clinical Validation: Research evaluates model performance in clinical settings; validation and integration may require additional studies.
3. Focus on Brain Tissue and Tumor localization
4. Metrics for evaluation.

Conclusions:

In this study, brain tissue and tumor localization in MRI images were determined with the use of an optimization-based deep neural network. The model improved in terms of both its accuracy and its resilience, but it had drawbacks in terms of things like its capacity to generalize and be interpreted. Nevertheless, the technique shows potential for enhancing the diagnosis of neurological illnesses, as well as treatment planning and monitoring. In order to overcome these constraints and make it easier to put this findings into practice in clinical settings, more research and validation are required.

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