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Deep Learning based Medical Image Analysis using Small Datasets

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The emergence of deep learning (DL) has significantly improved the capabilities of medical image analysis, providing a basis for automated and accurate interpretation of imaging data. This work centers on the challenges and solutions related to the use of deep learning for medical image analysis in scenarios constrained by small datasets. DL algorithms exhibit remarkable performance when trained on large datasets. Yet, within the medical domain, the assembly of large, annotated datasets poses a big challenge. Obtaining such datasets is significantly impeded by privacy concerns, the rarity of medical conditions, and the time-intensive nature of gathering large annotated datasets. This thesis addresses these challenges by leveraging DL techniques designed to maximize learning from limited data.
This work presents a framework that employs attention mechanisms, suitable sampling strategies, modified loss functions, and optimizers to improve the effectiveness of Convolutional Neural Networks (CNNs) on limited datasets. In addition, preprocessing techniques such as resampling and histogram matching are used to mitigate shifts in the data distribution, enhancing model generalizability across different medical imaging sources.
In the first study, a deep learning methodology was devised for precise segmentation of Total Kidney Volume (TKV) in Autosomal Dominant Polycystic Kidney Disease (ADPKD) using MRI data, addressing the challenge of accurately estimating TKV, crucial for monitoring disease progression. This methodology incorporated attention mechanisms, the cosine loss function, and Sharpness-Aware Minimization (SAM) within a U-Net architecture to improve focus on relevant features, tackle small dataset limitations, and enhance model generalizability. Validated on 100 MRI scans, it demonstrated significant accuracy improvements, achieving a Dice similarity coefficient of 0.918, and showcased the efficacy of ensemble models for further accuracy enhancement.
The next study was an extension of the first study, where a generalizable algorithm for kidney segmentation was developed. Incorporating Nyul normalization, resampling, and attention mechanisms, this CNN framework demonstrated high generalizability and accuracy across varied patient datasets. Validated on two separate cohorts, it achieved significant improvements over the baseline model, underscoring its clinical potential for precise TKV calculation.
In the next study, an approach was developed for the automated prognosis of renal function decline in ADPKD patients using MRI data. Employing a dual-model strategy that integrates a CNN for kidney volume segmentation with attention mechanisms and an MLP for disease progression prediction, this method combines image and biomarker features. Validated on 135 patients, it achieved prognostic accuracies with area under the curve (AUC) scores exceeding 0.95 for predicting various stages of chronic kidney disease (CKD) and demonstrated a high correlation in predicting eGFR decline.
In the third study, an algorithm employing a 3D residual U-Net architecture integrated with histogram matching was developed for the detection and monitoring of Multiple Sclerosis (MS) through Voxel-Guided Morphometry (VGM) maps. This model, designed to accurately highlight MS-related brain structure changes in MRI volumes, demonstrated its adaptability and generalizability across unseen datasets. Validated on diverse patient datasets, it achieved an average improvement of 4.2% in Mean Absolute Error (MAE) over the reference method, confirming its robustness and potential as a clinical tool for precise, efficient MS lesion dynamics analysis.
In the final study, a CNN-based framework was developed to automate acute Abdominal Aortic Dissection (AD) detection in CT scans. This approach, trained on a small internal dataset, was further validated using a large external set. The model demonstrated a high AUC and sensitivity in detecting AD, confirming its reliability and potential to transform emergency radiology through AI-assisted diagnosis.

This thesis underscores the potential of deep learning in overcoming the limitations posed by small datasets in medical image analysis, paving the way for more accessible and efficient AI-driven diagnostics and therapeutic planning.