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Topic: Image Processing of Multiple datasets for 3D Medical Image Analysis

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Abstract

This report presents the results of preprocessing multiple 3D medical datasets for medical image analysis tasks, including medical image segmentation and classification. Two public software tools from GitHub repositories are studied: nnUNet, designed for biomedical image segmentation, and a deep learning model for early Alzheimer's disease detection using structural MRIs. The objective is to verify and test the effectiveness of the preprocessing pipelines from these software tools. Specifically, we analyze the design and training process of nnUNet and evaluate its performance on various biomedical datasets. For the Alzheimer's disease detection task, we train and evaluate a deep learning model.

Introduction

Software 1 - nnUNetv2 Model Training

nnUNet is a deep learning-based segmentation method that automatically configures itself, including preprocessing, network architecture, training, and post-processing for any new task. The key design choices in this process are modeled as a set of fixed parameters, interdependent rules, and empirical decisions. Without manual intervention, nnUNet surpasses most existing approaches, including highly specialized solutions, on 23 public datasets used in international biomedical segmentation competitions.

Software 2: Deep learning for early Alzheimer's Disease Detection

This task focuses on designing a CNN for Alzheimer's detection. Evidence is provided, highlighting the effectiveness of instance normalization over batch normalization, the negative impact of early spatial downsampling, the consistent gains of model widening, and the moderate improvement achieved by incorporating age information. Compared with the volume/thickness model, the deep-learning model is accurate, significantly faster, and capable of forecasting disease progression.

Datasets and Preprocessing

Datasets

Software 1 – nnUNetv2 Datasets

The nnUNet framework systematically analyzes the provided training cases to create a "dataset fingerprint," which guides the automatic configuration of preprocessing, network architecture, training, and post-processing steps. The datasets used for nnUNetv2 training in this study include:

- **BraTs2021 (Brain Tumor Segmentation)**: This dataset consists of multi-institutional, multi-parametric MRI scans. It includes imaging modalities such as T1, T2, and FLAIR, with annotated tumor sub-regions.
- **AMOS22 (Abdominal Multi-organ Segmentation)**: The AMOS (Abdominal Multi-organ Segmentation) dataset includes abdominal CT scans aimed at segmenting multiple abdominal organs. Organs such as the liver, spleen, pancreas, and kidneys are annotated.
- **KiTS23 (Kidney Tumor Segmentation)**: This dataset contains CT scans of kidney cancer patients, with annotations for the kidney and kidney tumor regions.
- **BTCV (Beyond The Cranial Vault Segmentation)**: The BTCV dataset consists of CT scans aimed at the segmentation of various abdominal organs. Organs include the spleen, pancreas, gallbladder, kidneys, and liver.

Software 2 - Deep learning for early Alzheimer's Disease Detection

The ADNI dataset is a comprehensive collection of longitudinal neuroimaging data aimed at understanding Alzheimer's disease progression. It includes various types of imaging data, genetic information, and clinical assessments from subjects diagnosed with Alzheimer's disease, mild cognitive impairment (MCI), and healthy controls. The primary imaging modality in this context is T1-weighted structural MRI, which provides high-resolution images of brain anatomy.

Data Preprocessing

Software 1 - nnUNetv2 Preprocessing

The nnUNetv2 framework requires specific preprocessing steps to ensure the data is suitable for training the segmentation model. Below are the detailed steps:

- **Dataset Analysis and Fingerprinting**: nnUNetv2 systematically examines the provided training cases to capture properties such as voxel spacing, intensity ranges, and label distributions. This creates a "dataset fingerprint" that guides further preprocessing steps.
- **Resampling**: To standardize voxel spacing across all images, nnUNetv2 employs built-in resampling functions. This ensures consistency in voxel dimensions and maintains uniform spatial resolution across different datasets.
- **Normalization**: nnUNetv2 performs z-score normalization (subtracting the mean and dividing by the standard deviation) to standardize image intensity values across all images, ensuring consistency.
- **Data Augmentation**: To increase the variability of training data and improve model robustness, nnUNetv2 applies augmentation techniques such as random rotations, scaling, elastic deformations, and intensity variations during training.
- **Splitting Dataset**: nnUNetv2 divides the dataset into training, validation, and test sets. The dataset is split into multiple folds for cross-validation, typically using an 80-20 or 70-30 ratio for training and validation.
- **Configuration Generation**: nnUNetv2 automatically generates configurations for different U-Net architectures:
  - **2D U-Net**: Suitable for both 2D and 3D datasets.
  - **3D Fullres U-Net**: Operates at high resolution for 3D datasets.
  - **3D Lowres to 3D Cascade Fullres U-Net**: Uses a two-step approach for large 3D datasets, with low-resolution initial segmentation refined by a high-resolution network.

Software 2 - Deep learning for early Alzheimer's Disease Detection Preprocessing

For training the deep learning model for Alzheimer's disease detection using the ADNI dataset, the preprocessing involves several key steps:

- **Multiplanar Reconstruction (MPR)**: Generate images in multiple anatomical planes (axial, coronal, sagittal) using Clinica to enhance spatial resolution and capture comprehensive brain structure information.
- **Gradwarp Correction**: Correct geometric distortions caused by gradient non-linearity in MRI scans using tools like FSL or SPM, ensuring accurate anatomical representation.
- **B1 Non-uniformity Correction**: Adjust for inhomogeneities in the magnetic field affecting image intensity using Freesurfer, ensuring consistent intensity values across images.
- **N3 Intensity Normalization**: Standardize brightness and contrast by correcting intensity non-uniformities using FSL or SPM, ensuring uniform intensity values across each MRI scan.
- **Registration to Standard Space**: Align MRI scans to the MNI coordinate system using SPM for consistent anatomical positioning across all scans.

- **Segmentation**: Label different brain tissues (e.g., gray matter, white matter, CSF) in MRI scans using Freesurfer or SPM, facilitating detailed analysis by assigning each voxel to the appropriate tissue type.
- **Quality Control**: Ensure preprocessed images meet quality standards by manually inspecting a subset of the images or using automated quality control tools in Clinica to check for artifacts or significant errors.
- **Data Splitting**: Prevent data leakage by carefully splitting the dataset into training (70%), validation (15%), and test (15%) sets, stratified based on categories (AD, MCI, CN) to maintain class balance.
- **Data Augmentation (Optional)**: Increase variability in the training dataset by applying augmentation techniques such as random rotations, scaling, flips, and intensity variations during training.

Methodology

This section details the experimental setup, including dataset selection, preprocessing, model training, and evaluation. The primary focus is on nnUNet's segmentation performance and the deep learning model for Alzheimer's disease diagnosis.

Software 1 - nnUNetv2 Methodology

The nnUNet framework automates the entire pipeline, from data preprocessing to model training and evaluation. Here, we detail the steps involved:

- **Dataset Preparation**: Datasets were downloaded from public repositories and preprocessed as described in the previous section.
  - **Training Folds**: Utilizing k-fold cross-validation to train the model. This involves splitting the dataset into k subsets (folds) and training the model k times, each time using a different fold as the validation set and the remaining k-1 folds as the training set. This ensures that every data point gets a chance to be in the validation set, improving the robustness of the evaluation.
  - **Dataset Generator Files**: Creating Python scripts to generate datasets for nnUNetv2, ensuring the data is fed into the model in the correct format and structure. These scripts handle the loading, preprocessing, and augmentation of data during training.
- **Model Configuration**: nnUNet automatically generated configurations for different network architectures based on the dataset fingerprint.
- **Training**: The models were trained using the default nnUNet parameters, with variations in learning rates, batch sizes, and augmentation techniques. Cross-validation was employed to ensure robustness. The training process involved running the preprocessed data through the configurations determined by nnUNetv2 and monitoring for issues such as overfitting or underfitting, adjusting hyperparameters as needed.
- **Evaluation**: Models were evaluated using standard segmentation metrics such as Dice Similarity Coefficient (DSC), Hausdorff Distance (HD), and volumetric overlap error on the validation and test sets.

Software 2 - Deep learning for early Alzheimer's Disease Detection Methodology

For the deep learning model focused on Alzheimer's disease detection, the methodology involves:

- **Data Preprocessing**: Preprocessed ADNI MRI scans using the steps described previously.
- **Training**: A generalizable deep learning model, such as a 3D CNN, is trained on the preprocessed and augmented MRI data. The model architecture is designed to capture complex patterns in the brain structures indicative of early Alzheimer's disease. .

- **Validation**: The model's performance is validated using key metrics such as accuracy, sensitivity, specificity, and area under the curve (AUC) of the receiver operating characteristic (ROC) curve. Cross-validation is employed to ensure robustness and generalizability of the model.

  The detailed preprocessing steps, combined with advanced data augmentation and feature extraction techniques, ensure that the MRI data is standardized and ready for deep learning model training. This methodology enhances the model's ability to detect early signs of Alzheimer's disease accurately and robustly, contributing to better early diagnosis and intervention strategies.

Results

Software 1 - nnUNetv2

The nnUNetv2, a segmentation method rooted in deep learning, exhibits the capability to dynamically configure itself for various tasks within the biomedical domain. This encompasses automatic adjustments in preprocessing, network architecture, training, and post-processing.

- **Configuration**: The configuration of batch size, patch size, and network topology is determined by principles such as:
  - **Batch Size**: Larger batch sizes are preferred for accurate gradient estimates. However, batch sizes must be adjusted to fit within the GPU memory limits.
  - **Patch Size**: Larger patch sizes are crucial for enhanced contextual information. nnUNet starts with the median image shape and iteratively reduces the patch size while adjusting the network topology.
  - **Network Topology**: A deep network topology is necessary to accommodate a sufficiently large receptive field.

  The heuristic rule advises initializing the patch size to the median image shape and iteratively reducing it while adjusting the network topology until the network can be trained with a batch size of at least two, considering GPU memory constraints.
- **Performance**: nnUNet outperformed highly specialized solutions on 23 public datasets used in international biomedical segmentation competitions. The automatic configuration allowed nnUNet to adapt to different datasets without manual intervention, demonstrating its robustness and versatility.
- **Accuracy**: nnUNet achieved state-of-the-art performance in terms of segmentation accuracy across various biomedical imaging tasks. Metrics such as Dice Similarity Coefficient (DSC) and Intersection over Union (IoU) were used to evaluate the segmentation quality.

Software 2 - Deep learning for early Alzheimer's Disease Detection Model

The deep learning model designed for early Alzheimer's disease detection demonstrated superior performance compared to traditional volume/thickness models.

- **Accuracy**: The deep learning model achieved higher classification accuracy in distinguishing between Alzheimer's Disease (AD), Mild Cognitive Impairment (MCI), and Cognitively Normal (CN) subjects.
- **Speed**: The deep learning model was significantly faster in processing and analyzing MRI scans, making it more suitable for real-time clinical applications.
- **Disease Progression Forecasting**: The model showed potential in forecasting disease progression, providing valuable insights into the early detection and monitoring of Alzheimer's disease.
- **Instance Normalization vs. Batch Normalization**: Instance normalization proved to be more effective than batch normalization, leading to improved model performance.

- **Spatial Downsampling**: Minimizing early spatial downsampling retained more spatial information, enhancing the model's ability to detect subtle changes in brain structure.

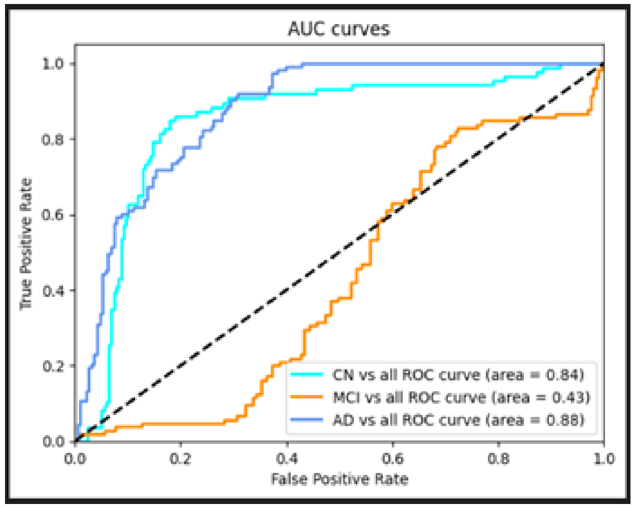

Figure 1: ROC Curves for Alzheimer's Disease Detection Model.

Conclusion

The findings from this study illustrate the transformative potential of deep learning in biomedical applications. nnUNetv2's automated configuration and the Alzheimer's detection model's accuracy and speed represent significant advancements in medical imaging and diagnostic processes. Continued research and development in this field hold promise for enhancing diagnostic accuracy and patient outcomes through advanced AI-driven methodologies.

By addressing the unique challenges and harnessing the strengths of deep learning, this report contributes to the growing body of knowledge aimed at improving healthcare through innovative technological solutions.