

**UNSUPERVISED CROSS-MODALITY DOMAIN  
ADAPTATION FOR MULTI-CLASS SEGMENTATION  
IN MRI**

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Thesis submitted in partial fulfillment of the requirements for the degree.

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Name of the supervisor: Dr. Charith Chitraranjan

Signature of the supervisor:

Date :

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## ABSTRACT

This research explores the Unsupervised Cross-modality Domain Adaptation approach for multiclass segmentation in Magnetic Resonance Imaging (MRI). Medical image segmentation is a challenging task when it's implemented in real-world applications. When comes to MRI, there is a massive variation in images due to the parameters, machine types, etc. As a result, the target datasets have a different intensity distribution compared to the training dataset. Similarly, due to the lack of labeled datasets, it's difficult to train more generalized models. So cross-modality domain adaptation aims to address these challenges by exploiting labeled data from the source domain to train a segmentation model that can be applied in a different and unlabeled target domain.

The proposed method synthesizes target domain images using two unpaired image-to-image translation techniques, namely the CycleGAN and CUT models. Then based on the evaluation of the ResNet-based domain discriminator best-synthesized images are selected and trained in the nnUNet segmentation model. Self-training is used to improve the model's accuracy and robustness. During the research, seven methods were evaluated, and final results were generated by combining two models through an ensemble approach.

Experiments were conducted on the publicly available annotated dataset of Vestibular Schwannoma (VS); the tumor and the nearest Cochlea. The dataset includes two types of MRI images: contrast enhanced T1 (ceT1) and high-resolution T2 (hrT2). The ceT1 modality was used as the source domain, including images and their corresponding labels, while the hrT2 modality was used as the target domain, consisting of unpaired images. The results show that the proposed method reduces the gap between supervised segmentation and unsupervised segmentation and achieves performance comparable to supervised methods.

Overall, this thesis contributes to the development of robust and accurate segmentation models for medical imaging, which can be used for clinical applications such as diagnosis, treatment planning, and monitoring of disease progression.

**Keywords:** Unsupervised Domain Adaptation, Segmentation, Vestibular Schwannoma, Cochlea, MRI

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## LIST OF ABBREVIATIONS

<b>Abbreviation</b>	<b>Description</b>
ML	Machine Learning
DL	Deep Learning
VS	Vestibular Schwannoma
MRI	Magnetic Resonance Imaging
DA	Domain Adaptation
DANN	Domain-Adversarial Neural Network
CUT	Contrast Unpaired Translation

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