# Challenges in Domain Adaptation for Medical Image Segmentation


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## 1. Background

- Hip X-ray image segmentation is critical for medical diagnosis but faces challenges due to variations across hospital datasets.
- Inconsistencies arise from differences in image resolution, cropping, contrast, exposure, and anatomical factors (e.g., age, gender, disease progression).
- These variations degrade segmentation model performance, necessitating domain adaptation techniques to ensure robustness across diverse datasets [1].

## 2. Research question

How effective is supervised domain adaptation in improving the generalization of deep learning models for medical image segmentation across different datasets ?

## 3. Methodology and experiments

- **Base Model Used:** U-Net architecture, a convolutional neural network [2].
- **Datasets:** Cohort Hip and Cohort Knee (CHECK) dataset and the Osteoarthritis Initiative (OAI) dataset.
- **Data Preprocessing:** Intensity normalization, image resizing and ground truth generation with BoneFinder.
- **Evaluation metrics used:** Dice score and Hausdorff distance.
- **Baseline performance:** Test show **no significant domain shift** between CHECK and OAI.
  - ➢ Introduce artificial domain shift with gamma transform to simulate different imaging conditions.

Figure 1: original OAI input

Figure 2: Ground truth

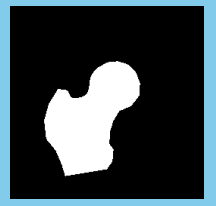

Figure 3: Gamma=0.5

- **Supervised domain adaptation:** Train the model on the source (CHECK) and a percentage of the training data is taken from the target (OAI) for better adaptability to this domain shift.
- For 3 different gamma values, and 6 different proportions of target data in training, each model is tested on both CHECK and OAI, to assess the ability of the adapted model to perform well on both.
- Each model is also trained using adequate batch weights to balance the small proportion of target data.

## 4. Results

- Supervised domain adaptation did not significantly enhance segmentation accuracy
- The accuracy sometimes even dropped, particularly when using small amounts of target data.
- Weight balancing failed to improve the segmentation accuracy

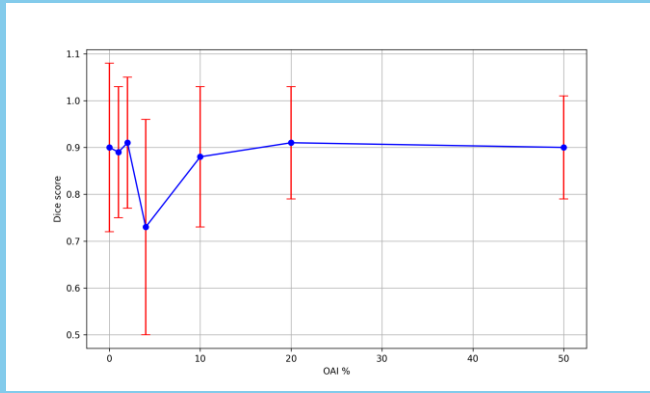


Figure 4: Dice Scores for Varying OAI Data Percentages

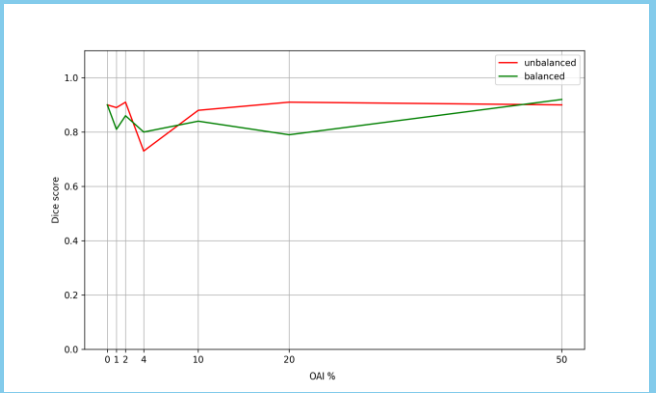


Figure 5: Dice Scores: Balanced vs. Unbalanced

## 5. Conclusions

- **Key Findings:** Supervised domain adaptation did not consistently improve segmentation performance across both datasets.
- **Implications:** We found limited practical benefits of domain adaptation in this specific context. We doubt its assumed effectiveness in reducing clinician workload for osteoarthritis diagnosis.
- **Future Work:** Explore alternative domain adaptation techniques or combinations to achieve more consistent generalization and reliability in X-ray Bone segmentation.

## 6. References


[1] A. L. Martel and et al. Medical Image Computing and Computer Assisted Intervention - MICCAI 2020. Springer Science+Business Media, 2020.
[2] Olaf Ronneberger, Philipp Fischer, and Thomas Brox. U-net: Convolutional networks for biomedical image segmentation, 2015.