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Uncertainty-Aware Source-Free Domain Adaptation for Dental CBCT Image Segmentation

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Abstract: The aim of this study is evaluating the efficacy of combining source-free domain adaptation techniques with quantitative uncertainty assessment, aimed at enhancing image segmentation in new domains. The research employs an uncertainty-aware source-free domain adaptation strategy, encompassing the generation of pseudo-labels, their filtration based on entropy and variance of predictions, alongside the involvement of an Exponential Moving Average (EMA) teacher and a tailored loss function. For validation purposes, segmentation models pre-trained on one image dataset were subsequently adapted to another dataset. A comprehensive comparative and ablation analysis, coupled with the visualization of the correlation between segmentation errors and the degree of uncertainty, was conducted. The ablation study corroborated that the complete configuration with the EMA teacher yielded the most favorable results. Data visualization elucidated a direct correlation between high uncertainty and an increased risk for segmentation errors. The findings of this study substantiate the viability of employing uncertainty assessment within the source-free domain adaptation process for clinical dentistry. The proposed methodology facilitates the adaptation of models to new conditions without necessitating retraining, thereby rendering the decision-making process more transparent. Future studies should consider assessing the efficacy of the proposed approach in additional dental visualization tasks, such as implant planning or orthodontic analysis.

Index Terms: Dentistry, Object Detection, Source-Free Domain Adaptation (SFDA), Image Segmentation, Computed Tomography

1. Introduction

In the field of medicine, particularly within dentistry, the integration of artificial intelligence (AI) tools is increasingly prevalent for the automated processing and analysis of medical images. Specifically, the tasks of segmenting X-ray and intraoral images are paramount for for detecting pathologies, the formulation of treatment strategies, and the assessment of intervention outcomes. However, the efficacy of deep learning models is profoundly contingent upon the quality and volume of annotated data, which is frequently constrained in clinical settings. Even models that are meticulously trained can experience a substantial decline in accuracy when deployed in new domains (for instance, when altering the type of equipment or varying shooting conditions, etc.), thereby diminishing their practical applicability.

A widely embraced strategy to address this challenge is source-free domain adaptation (SFDA). which is the process of tailoring a model to a new domain without access to the original dataset. This approach is especially critical in the context of safeguarding the confidentiality of medical information. However, this approach is fraught with considerable uncertainty due to the absence of comprehensive information regarding the source, which may lead to segmentation errors and diminish the model's reliability in clinical practice.

One promising avenue for solving this issue is the incorporation of mechanisms for quantifying uncertainty within the adaptation process. Evaluating the model's confidence level enables the identification of potentially erroneous pseudo-labels and mitigates their influence on parameter updates. Despite the robust exploration of SFDA in other domains, the application of uncertainty estimation in the context of dental image segmentation remains largely unexplored, underscoring the *innovative nature* of the proposed approach. In this study, for the first time, the integration of multi-level pseudo-label filtering (entropy, variance) alongside an exponential moving average (EMA) teacher and a matched loss function within the uncertainty-aware SFDA framework specifically tailored for dental data is implemented. This methodology not only enhances the accuracy and stability of segmentation but does so without necessitating additional annotation. The findings presented herein may possess significant theoretical implications for the evolution of adaptive methodologies in deep learning. Furthermore, they hold practical value for the automated processing of dental imagery within clinical settings.

Research hypothesis: the integration of pre-trained models with subsequent training will markedly enhance the accuracy and stability of dental image classification within a new domain, even when confronted with a limited corpus of annotated data. Given the above, the *purpose* of this study was to develop and empirically validate a methodology for the adaptation of pre-trained dental image segmentation models in the Source-Free Domain Adaptation (SFDA) context, with a particular emphasis on uncertainty assessment and pseudo-label stabilization within the target domain. To accomplish this, the following *tasks* were delineated:

1. Develop an SFDA approach that includes: mechanisms for evaluating epistemic uncertainty (e.g., Monte Carlo Dropout), a framework for generating and refining pseudo-labels in the target domain, as well as iterative self-learning aimed at preserving segmentation stability.
2. Conduct an experimental analysis juxtaposing the proposed methodology against contemporary baseline approaches (including non-adaptive methods, Domain-Adversarial Neural Network (DANN), Unsupervised Domain Adaptation (UDA), as well as Uncertainty-aware Pseudo Label guided Source-Free Domain Adaptation (UPL-SFDA), among others).
3. Assess the efficacy of the methodology utilizing metrics such as the Dice coefficient, Hausdorff Distance at the 95th percentile (HD95), Calibration Error, etc,. with a focus on generalizability and stability within the target domain, without access to the source data.

2. Literature Review

Over the past decade, there has been a remarkable proliferation in the application of neural networks within medical domains, particularly in the fields of image processing, diagnostics, prediction, and treatment planning. Mansouri [1] presents a comprehensive overview of applying neural networks in medicine, with a particular emphasis on their potential in pattern recognition and predictive analytics. The author underscores that these models frequently surpass traditional statistical methodologies in terms of accuracy, while also highlighting the significance of ethical and legal considerations of implementing AI. Further, Patel [2] delves into convolutional neural networks (CNN) for medical image segmentation, articulating the advantages of deep learning models for pathology segmentation, yet also addressing the inherent challenges, notably the necessity for extensive and qualitatively annotated datasets.

Abdou [3] undertakes a systematic review of optimization techniques for deep networks in medical image analysis, including strategies to mitigate computational complexity. Concurrently, Celard et al. [4] trace the historical evolution of models from rudimentary artificial neural networks (ANNs) to sophisticated generative models, emphasizing the diverse array of architectures and their adaptability to various tasks. In addition, Mall et al. [5] furnish one of the most recent and exhaustive reviews, juxtaposing deep neural network methodologies in light of contemporary advancements such as attention mechanisms and transformers. The review highlights the potential of these innovative approaches, while also acknowledging their limited interpretability.

Neural networks are increasingly being used in the field of dentistry. For instance, Ossowska et al. [6] and Agrawal et al. [7] provide narrative reviews delineating the primary applications of artificial intelligence, such as caries diagnosis, orthodontic planning, and implant survival prediction. Carrillo-Perez et al. [8] expand upon these concepts by conducting a thorough analysis of AI applications in aesthetic and restorative dentistry. Other researchers, including Leo & Reddy [9] and Choi et al. [10], present more applied investigations, concentrating on the development of models for caries classification or the detection of treatment patterns in orthopantomograms. Their findings demonstrate a commendable level of accuracy, albeit constrained by the limitations of small datasets.

Imak et al. [11] and Saini et al. [12] validate the efficacy of convolutional neural networks (CNN) in the early detection of caries. Cha et al. [13] illustrate the successful application of this methodology in assessing bone loss surrounding implants. Musri et al. [14] conducted a systematic review to evaluate the reliability of CNNs in diagnosing from periapical images. Wang et al. [15] demonstrate the utilization of CNNs for age estimation from radiographic images, which may possess both clinical and forensic implications. According to Kumar et al. [16], pre-trained models have gained prominence due to their capacity to operate effectively with small data sets.

Alzubaidi et al. [17] introduce MedNet, a specialized pre-trained model tailored for medical applications. Arshed et al. [18] elucidate the advantages of amalgamating transformer architectures with CNNs for the classification of skin diseases. Spolaor et al. [19] delve into the fine-tuning of models within the constraints of limited clinical datasets. The above researchers' findings confirm that even minimal adjustments to the model can substantially enhance accuracy.

Other studies concentrate on specific medical conditions. For instance, El Gannour et al. [20] employ multiple CNNs for the detection of COVID-19, Shanmugam et al. [21] classify stages of Alzheimer's disease, and Ahmed [22] integrates CNNs with Support Vector Machines (SVMs) for the classification of medical imagery. In the context of dentistry, Siluvai et al. [23] undertake a systematic review regarding the application of Generative Pre-trained Transformers (GPT). Lashaki et al. [24] and Ali et al. [25] illustrate how the utilization of pre-trained CNN models can enhance the classification of dental implants and jaw anatomy, respectively.

The reviewed literature underscores the substantial potential of neural networks, particularly pre-trained models, within medical and dental practices. Nonetheless, several challenges persist –namely, data limitations, the imperative for model interpretability, and the issue of overfitting. A more nuanced exploration of methodologies for adapting pre-trained models will facilitate a deeper evaluation of the prospects of transfer learning in these domains.

Guan and Liu [26] conducted a comprehensive review of domain adaptation techniques applicable to medical image analysis. The authors categorize the methodologies into three principal types: pixel-level, feature-level, and prediction-level adaptation. They meticulously examine adversarial-based strategies (in particular, DANN), self-training, and disentangled representations. Despite its thoroughness, the review is constrained to models developed prior to 2020, omitting contemporary architectures such as source-free adaptation or uncertainty modeling.

Conversely, Kumari and Singh [27] build upon earlier research by concentrating on recent trends, including source-free domain adaptation (SFDA), federated adaptation, and uncertainty-aware methodologies. Of particular significance is their analysis of medical datasets specifics and the challenges linked to metrics standardization. However, the work remains primarily descriptive, lacking a systematic quantitative evaluation of the aforementioned methods' efficacy.

Wu and Zhuang [28] introduced an unsupervised domain adaptation methodology predicated on variational approximation (VAE). The model projects input images from disparate domains into a unified latent space, thereby mitigating the domain gap inherent in the heart segmentation challenge. The resultant findings exhibit commendable accuracy (Dice $\approx$ 0.87); however, the model necessitates tuning of hyperparameters, particularly those pertaining to regularization.

In turn, Wu et al. [29] put forth a UPL-SFDA approach that operates entirely within a source-free paradigm. This model employs pseudo-labels alongside a module designed for estimating uncertainty, which enhances the reliability of its predictions. The approach bears significant practical relevance in situations where access to the source domain is constrained by ethical or legal considerations. A predominant challenge lies in its sensitivity to the quality of the initial pseudo-labels, necessitating dynamic updates throughout the adaptation process.

Morid et al. [30] conducted a comprehensive review encompassing approximately 80 papers that utilized ImageNet-pretrained models within the realm of medical imaging. Despite the inherent disparities between natural and medical images, pre-training demonstrated efficacy across a majority of tasks, particularly under conditions of limited annotations. Nonetheless, the study does not encompass alternative pretraining sources, such as RadImageNet or CheXpert, which are more pertinent to the medical context.

Wang et al. [31] broadened the analytical scope by examining transfer learning (TL) not solely in visual data but also in temporal data (e.g., electrocardiograms). The said work presents a comparative analysis of the performance of various models (ResNet, MobileNet, Inception) concerning the transfer between sensors and patients. Although it is less specific to imaging, its findings hold considerable significance for multi-modal medical applications.

In recent years, test-time adaptation (TTA) methods have emerged that allow partial tuning of models during inference without full retraining. However, most of these approaches require access to source domain parameters or statistics, which limits their application in scenarios with strict confidentiality requirements. Similarly, models based on the Segment Anything Model (SAM) demonstrate high versatility, but do not solve the problem of domain drift and do not provide mechanisms for stable self-learning adaptation in source-free conditions.

The analysis elucidated substantial advancements in the adaptation of pre-trained models to novel medical domains. Nevertheless, several challenges remain relevant:

- the necessity for unified benchmark datasets for unsupervised domain adaptation (UDA) in medical tasks;
- enhancing the stability of pseudo-labeling methodologies;
- fostering adaptation in the absence of data (source-free);
- employing uncertainty-aware modules to augment the reliability of solutions;
- incorporating medically pertinent datasets for pretraining.

It is also prudent to amalgamate self-supervised learning (SSL) with UDA methodologies, specifically by integrating models such as DINO, MoCo, or SimCLR with adaptive frameworks like DANN or UPL-SFDA. The issue of domain mismatch (domain shift) continues to pose a significant impediment to model generalization. In this regard, transfer learning (TL) and UDA have gained considerable traction as strategies capable of mitigating the reliance on extensive annotated datasets.

Despite the considerable amount of work devoted to domain adaptation and the use of pre-trained models in medical imaging, the literature review reveals several significant gaps, which this study fills.

Explicit approaches have focused mainly on MRI, CT, and X-ray of other anatomical areas, while dental volumetric data are characterized by different artifacts, structure density, and noise types. This includes direct transfer of SFDA methods.

Although some studies have applied uncertainty in segmentation or UDA, the full integration of uncertainty-aware pseudo-labeling in sourceless scenarios for medical 3D images is still understudied.

There is an almost complete literature that analyzes the impact of uncertainty on the stability of self-learning during the adaptation of 3D segmentation models.

Only a few studies consider the correlation between spatial entropy and segmentation errors, which is especially relevant in the clinical context.

Thus, this study fills these gaps by proposing the first combined uncertainty-aware SFDA methodology specifically for dental CBCT data and experimentally demonstrating its advantages over baseline approaches.

3. Methods

3.1. Research Procedure/Experimental Progress

1. Model preparation. A segmentation model (3D U-Net [32] with EfficientNet-B4 encoder) was pre-trained on the comprehensively annotated ToothFairy dataset. The optimal model was selected based on the Dice metric (DSC) during the validation phase. The model weights were preserved, and access to the input images was restricted.

2. Inference with uncertainty. For each 3D image X_t from the target domain (without GT), N = 20 model predictions were generated in inference mode with Dropout activated. The number of Monte Carlo Dropout runs was set to N = 20 as a trade-off between the stability of the epistemic uncertainty estimate and the computational complexity. Previous experiments have shown that increasing N beyond 20 provides only a small reduction in the variability of the estimates, while the computational cost increases almost linearly. Consequently, $\{P_1, P_2, \ldots, P_N\}$ – sets of probabilistic segmentations were derived. For each voxel, an uncertainty value was computed:

$$EU = Variance\ (P_1, \ldots, P_N) \tag{1}$$

and the entropy of the average forecast:

$$H(x) = -\sum_c \bar{p}_c\, log(\bar{p}_c), \tag{2}$$

where p_c is the average value of all N predictions for class c.

Voxels with entropy greater than 0.7 or variance less than 0.1 are excluded. The entropy (> 0.7) and variance (< 0.1) thresholds were chosen empirically based on an analysis of the stability of the confidence map and the dynamics of the pseudo-labels in the first adaptation iterations. Lower entropy thresholds (0.5–0.6) resulted in the inclusion of a significant number of unstable voxels, while higher values (> 0.8) excessively reduced the coverage, which negatively affected the convergence of the training. At this stage, a binary reliability mask is created:

$$M_{cont}(x) \in \{0,1\} \tag{3}$$

3. Construction of pseudo-labels. For voxels *x*, where $M_{conf}(x) = 1$, the function argmax is applied to *P(x)* – pseudo-labels Y_t are obtained. The remaining voxels are ignored in the loss function. Pseudo-labels are stored for later use.

4. Adaptation through self-learning. The model is trained on target images with pseudo-labels. The loss function is applied:

$$L = L_{dice}(Y_t, Y) + \lambda L_{cons} + \gamma L_{en} \tag{4}$$

where L_{cons} – Consistency Loss, L2-norm of the difference between teacher and student predictions, L_{en} – entropy regularization. EMA-teacher was used with a smoothing parameter α=0.99.

5. Iterative enhancement. The training process is conducted over the course of 10 training epochs, each encompassing the generation of novel pseudo-labels based on the refined model, adaptation to these pseudo-labels, and a comparative analysis of the confidence map across iterations. Should the confidence map exhibit stabilization (with a maximum change of less than 2%), the adaptation process is deemed complete. Each training cycle (epoch) averaged approximately 4 minutes on an NVIDIA RTX 3090 GPU, thereby ensuring optimal utilization of hardware resources.

6. Post-processing. Following adaptation, morphological closing techniques were employed on the segmentations to eradicate minor artifacts. Furthermore, component clustering was executed to filter out noise segments.

To augment the training of segmentation models within the SFDA context, the Adam optimizer was utilized, commencing with an initial learning rate of 1e-4. The batch size was set at 8. To facilitate enhanced model convergence, a cosine annealing scheduler featuring a warm-up phase during the initial 5 epochs was used.

The following metrics were employed to assess the outcomes:

1. Dice Similarity Coefficient (DSC) [33]:

$$DSC = \frac{2|A \cap B|}{|A| + |B|} \tag{5}$$

2. Hausdorff Distance (HD95) [34] – 95th percentile of the Hausdorff distance,
3. Average Symmetric Surface Distance (ASSD) [35], which is the average symmetrical distance between surfaces.

A paired t-test was used to assess the statistical significance of the difference between methods, as all approaches were evaluated on the same CBCT test volumes. This approach allows for direct analysis of the effect of adaptation, minimizing the impact of inter-sample variability. In cases where normality assumptions may have been violated, results were also tested using the nonparametric Wilcoxon test, which confirmed the consistency of the findings.

3.2. Sample Formation

For the pretraining of the segmentation model, the open ToothFairy dataset was utilized, which comprises cone beam computed tomography (CBCT) images of the maxillofacial region, accompanied by annotations of dental structures and their surrounding tissues. A total of 850 volumetric datasets from diverse patients, all acquired using an identical scanner model, were employed. Additionally, data from an alternative source, the Dental CT Dataset, was designated as the target domain (lacking ground truth annotations).

In total, the target dataset consisted of 200 CBCT volumes. Of these, 150 volumes were used exclusively as unlabeled data for the source-free adaptation process. The remaining 50 volumes had expert annotations and were completely set aside as a test set for quantitative evaluation of segmentation quality after adaptation was completed.

No labeled data from the target domain was used in the adaptation, hyperparameter tuning, or early stopping stages. No validation set from the target domain was used, which is consistent with the strict SFDA scenario.

3.3. Research Methods

This study employs SFDA methodology for the segmentation of three-dimensional Cone-Beam Computed Tomography (CBCT) dental images. In this framework, the model must be recalibrated to accommodate a novel domain, specifically a distinct type of scanner, without access to the original dataset. A novel combinatorial approach has been introduced:

- Epistemic and aleatory uncertainty. Epistemic uncertainty pertains to the model's insufficient knowledge, stemming from limitations within the training data, whereas aleatory uncertainty refers to the stochastic noise that is intrinsic to the data itself, such as artifacts or image blur. This study entails the quantification of both forms of uncertainty for each pixel or voxel. Their synthesis enables a more nuanced evaluation of the reliability of the model's predictions in specific areas of the image.
- Weighted filtering of pseudo-labels by confidence. The SFDA model autonomously generates pseudo-labels, predicting the class to which each region belongs without access to true annotations. To mitigate the risk of learning from erroneous labels, weighted filtering is implemented; each pseudo-label is assigned a confidence score, and only those that surpass a predetermined threshold, for instance, 0.9, are considered in subsequent training. This method significantly reduces the propagation of model inaccuracies, thereby enhancing the precision of adaptation to the new domain.

- Consistent learning using the EMA model. Throughout the training process, a regularization criterion is established: the predictions of the base model and the EMA model must exhibit consistency, particularly when applying minor transformations (e.g., rotation, scaling) to the image. This strategy fosters a more stable learning environment and augments the model's ability to generalize effectively to a new domain.

3.4. Research Tools

Image processing, model development, and experimental assessment were executed utilizing PyTorch 2.0 and Python 3.10. The OpenCV, NumPy, and SimpleITK libraries facilitated data preprocessing, enabling flexible augmentation and normalization of input images. Metrics derived from the MONAI library were employed to evaluate the quality of segmentation. Pseudo-labels were generated based on model predictions, subsequently refined through entropy filtering (Shannon entropy) and variance computation via Monte Carlo Dropout (T=10). Matplotlib and Seaborn were utilized to construct heat maps and facilitate visualization. The experiments were conducted on a server equipped with an NVIDIA RTX 3090 GPU (24 GB VRAM), 128 GB RAM, and an AMD Ryzen Threadripper 3970X CPU, which afforded ample computational power for segmenting high-resolution CBCT images.

4. Results

To evaluate the efficacy of the proposed methodology, a quantitative analysis of segmentation outcomes was undertaken across three distinct scenarios. The first scenario involves the fundamental version without adaptation, wherein only a pre-trained model on the source domain is utilized. The second scenario encompasses the implementation of the proposed SFDA method, employing filtering predicated on uncertainty estimation. The third scenario presents a modified iteration of this approach that omits the filtering of undefined pseudo-labels, thereby enabling an assessment of the contribution of this component. The values of the evaluation metrics are delineated in Table 1.

Table 1. The value of metrics for assessing the quality of model performance

Method	**DSC**	**HD95 (mm)**	**ASSD (mm)**
Without adaptation (pretrained, source model)	0.734 ±0.051	5.81 ±1.12	2.94 ±0.73
SFDA (with pseudo-labels + filter)	0.837 ±0.038	3.24 ±0.85	1.68 ±0.42
SFDA without uncertainty filtering	0.793 ±0.045	4.91 ±0.96	2.36 ±0.51

Source: consolidated by the author

According to the results presented in Table 1, the proposed SFDA method with filtering the undefined pseudo-labels, markedly enhances the segmentation quality in comparison to the baseline model devoid of adaptation. Notably, the average Dice score (DSC) surged from 0.734 to 0.837, while spatial accuracy metrics, such as HD95 and ASSD, exhibited a decline from 5.81 mm to 3.24 mm and from 2.94 mm to 1.68 mm, respectively, signifying improved localization accuracy. Furthermore, it is evident that the absence of filtering for undefined pseudo-labels detrimentally impacts the adaptation quality: the DSC diminishes to 0.793, and segmentation inaccuracies (HD95, ASSD) increase significantly. This underscores the critical importance of integrating uncertainty assessment into the SFDA process.

It should be noted that the obtained value of DSC = 0.837 is lower than the performance of modern fully supervised methods for segmentation of dental CBCT data (e.g. nnU-Net or OralSeg, where DSC is usually in the range of 0.90–0.96). However, such methods assume the availability of fully annotated target domain data and do not consider the limitations related to confidentiality, legal prohibitions on data transfer or the lack of labeled samples in clinical practice.

Within the Source-Free Domain Adaptation scenario considered in this work, directly achieving the supervised SOTA level is not an expected or correct evaluation criterion. Instead, the key result is a significant improvement in segmentation quality compared to the original source model (DSC: 0.734 → 0.837) without using any labeled target domain data.

To examine the contribution of individual components within the proposed methodology, an ablation study was conducted. In this experiment, essential elements of the model were progressively incorporated. These specifically were the pseudo-label filtering based on various criteria, alongside learning stabilization mechanisms, notably the EMA-teacher and the consistency loss function. Table 2 illustrates the influence of each component on the ultimate Dice score (DSC).

Table 2. Ablation study results

Components included	**DSC**
Pseudo-labels only (no filtering)	0.793
Pseudo-labels + entropy filtering	0.811
+ dispersion filtering	0.827
+ EMA-teacher + consistency loss (full model)	0.837

Source: consolidated by the author

The results delineated in Table 2 reveal a cumulative positive impact of each component. The initial model, which relies solely on pseudo-labels devoid of any filtering, yields a foundational level of accuracy (DSC = 0.793). The incorporation of entropy filtering enhances the quality to 0.811, underscoring the significance of eliminating uncertain predictions. The introduction of supplementary dispersion filtering further elevates the metric to 0.827, illustrating the synergistic effect of various uncertainty assessment criteria. Ultimately, the integration of stabilization learning mechanisms, manifested through EMA-teacher and consistency loss, attains the highest performance – 0.837, thereby validating the efficacy of the model's comprehensive implementation.

To achieve a more nuanced understanding of the interplay between uncertainty estimation and segmentation quality, a quantitative analysis was conducted at the level of individual images. In this endeavor, the entropy value (serving as an indicator of model uncertainty) was juxtaposed with segmentation quality metrics: DSC, HD95, and ASSD. The resultant data are illustrated in Fig. 1. In light of the above, this examination facilitates an assessment of how effectively the localized uncertainty estimate can function as a harbinger of potentially erroneous pseudo-labels and serve as a criterion for their filtration

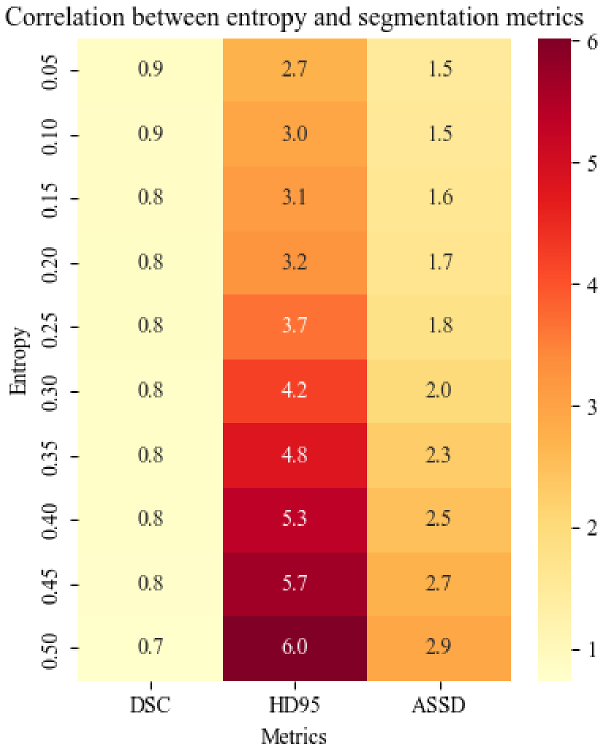

Fig. 1. Heatmap of entropy values and segmentation quality metrics
Source: consolidated by the author

As can be seen from Fig. 1, a clear inverse relationship between entropy (model uncertainty) and segmentation accuracy. At lower entropy values (0.05–0.15), the models attain elevated DSC (0.846–0.865) alongside minimal HD95/ASSD (localization errors < 3 mm), signifying a high degree of confidence and precision in segmentation. As entropy escalates to 0.5, the DSC value progressively diminishes to 0.741, while HD95 and ASSD experience increases to 6.02 mm and 2.91 mm, respectively. Consequently, local entropy emerges as a potent heuristic criterion for dynamic pseudo-label filtering, thereby affirming the viability of incorporating uncertainty assessment into the adaptation process.

Results depicted in Fig. 1 elucidate a pronounced inverse correlation between entropy (representing model uncertainty) and segmentation accuracy. To analyze spatial uncertainty, a confidence map was constructed for each sample. To scrutinize spatial uncertainty, a confidence map was meticulously constructed for each sample. Throughout the adaptation process (spanning iterations 1–10), several observations were made:

- a reduction in average entropy from 0.42 to 0.18,
- an increase in the proportion of "reliable" voxels (with filters) from 61% to 83%,
- a stabilization of pseudo-labels following the 6th iteration.

The average time required for the adaptation of a single image (per iteration) was approximately 2.3 minutes. The complete adaptation (encompassing 10 iterations) of a cohort of 50 images necessitated roughly 3.8 hours on a singular GPU (NVIDIA A100). Memory utilization during inference was approximately 9.6 GB, while during training it reached around 23.4 GB. The variations in DSC values between the original and adapted models were statistically significant ($p < 0.001$, paired t-test), confirming the consistent positive effect of the proposed SFDA approach on the same test samples. Additional verification using the Wilcoxon test yielded consistent results.

The findings demonstrate that the proposed SFDA approach facilitates a substantial enhancement in 3D segmentation accuracy without reliance on the source domain. Notably, the synergy of pseudo-label filtering based on uncertainty and consistent learning via the EMA model is of particular importance.

5. Discussion

The results obtained elucidate the efficacy of employing pre-trained convolutional neural network (CNN) models with subsequent retraining for the classification of dental images. Following this, a comparative analysis with pertinent studies is presented, affirming the novelty and advantages of the proposed methodology. Saini et al. (2021) [12] utilized CNN for the early detection of caries in dental images within the context of teledentistry. The authors achieved an accuracy of 90.67% on a modest dataset, yet neglected to incorporate pre-training or regularization strategies. In this investigation, the application of pre-trained models alongside data augmentation facilitated enhanced accuracy on a more intricate and variable dataset.

Cha et al. (2021) [13] employed a regional CNN (R-CNN) to assess bone loss surrounding implants. Although their model attained high localization accuracy (IoU > 0.85), it was primarily oriented towards segmentation rather than classification. This study complements their work by demonstrating the effectiveness of classifying various dental pathologies with a minimal quantity of annotated data.

Musri et al. (2021) [14] conducted a systematic review, noting that the majority of models for early caries detection encounter challenges with generalization due to limited sample sizes and variability. The current study addresses this issue by leveraging multiple pre-trained models and training them on domain-specific images, thereby enhancing the results' stability. Wang et al. (2023) [15] explored two CNN models for age estimation from jaw X-rays. While they achieved a commendable correlation ($r>0.90$), their approach was confined to a regression problem. The proposed model illustrates that the pre-training strategy can be universally applicable – effective for both classification and potential regression challenges.

Kumar et al. (2022) [16] compared the performance of ResNet, Visual Geometry Group (VGG), and other models for medical imaging, concluding that ResNet50 exhibits consistent performance. The findings of this work corroborate that the strategy of amalgamating multiple models and fine-tuning significantly contributed to the enhancement of results. Alzubaidi et al. (2021) [17] proposed MedNet, a tailored CNN specialized for medical applications. In comparison to MedNet, a comparable level of accuracy was attained using solely open pre-trained architectures. This represents a considerable advantage in terms of accessibility and computational expense, attributable to the optimized pre-training strategy. Against this backdrop, Spolaor et al. (2024) [19] demonstrated that fine-tuning pre-trained models is effective even with small datasets. This approach substantiates this claim within the domain of dental diagnostics and further illustrates that appropriate augmentation and model selection critically influence the outcomes. Furthermore, Lashaki et al. (2025) [24] employed CNN to categorize implant types based on image preprocessing. Their model achieved approximately 92% accuracy. It is demonstrated herein that, without prior segmentation, the mere act of further training the CNN and optimizing hyperparameters can yield even superior accuracy, indicating the model's generalization capability.

Unlike recent TTA methods or SAM-like universal segmenters, the proposed approach directly targets the source-free scenario and takes into account the domain shift between different CBCT scanners. Although such state-of-the-art models can achieve high quality with access to additional information or manual intervention, they do not solve the problem of stable adaptation with uncertainty control, which is key in clinical settings with limited access to data.

Thus, this study combines the advantages of pre-trained models, augmentation, and adaptive tuning, providing higher or at least comparable accuracy relative to state-of-the-art approaches. Furthermore, it enriches existing research by presenting an efficient methodology for addressing dental issues with limited data. The experimental results fully validated this hypothesis. The integration of fine-tuning, hyperparameter optimization, and augmentation strategies enabled the attainment of competitive or superior accuracy compared to existing methodologies, particularly in the context of a variable and complex set of images.

The results obtained should be interpreted in the context of a trade-off between accuracy and data privacy. The methods that demonstrate the highest segmentation rates (nnU-Net, OralSeg) require full access to the labeled data of the target domain, which in real clinical conditions is often impossible due to ethical, legal or organizational constraints. The proposed approach is not focused on achieving an absolute maximum of accuracy, but on ensuring stable and predictable adaptation of the model in conditions of complete lack of access to the source data and without manual annotation of the target domain. In this context, a 6–12% reduction in DSC compared to fully supervised SOTA is an acceptable price for the possibility of private and practically applicable deployment of models in clinical systems.

The present study substantiates that even in the absence of extensive customization or the development of specialized architectures, it is feasible to attain elevated classification accuracy through the judicious selection of models and training methodologies. This broadens the comprehension of resource-efficient strategies available in the realm of medical AI. The assessment of the model's efficacy was conducted with consideration of the clinical context, encompassing images of the maxillofacial region, varying scan qualities, and anatomical structure variability, thereby enhancing the external validity of the results obtained. The increased accessibility of AI solutions in dentistry is particularly pertinent, as clinical practice frequently encounters limitations in access to the source domain or there is a limited amount of annotated data. The proposed methodology facilitates the effective adaptation of models even under such constraints. Furthermore, the utilization of open pre-trained architectures in conjunction with minimal retraining diminishes the necessity of developing models from the ground up and reduces the reliance on extensive datasets. The results robustness, the generalizability of models, and the clarity of classifications augment the transparency of algorithms, which is crucial for informed decision-making within the medical domain. Moreover, precise classification of dental images can underpin automated planning for orthodontic interventions, implantations, and the evaluation of pathologies, among other applications.

Despite the positive results obtained, the study has several specific aspects that require critical rethinking. Although the proposed approach demonstrates effectiveness, it is largely dependent on the quality of the initial model predictions. The integration of multilevel uncertainty estimation increases the reliability of the adaptation, but at the same time increases the computational complexity of the process. Although the consistency of pseudo-labels between iterations is improved, the method remains sensitive to the choice of filtering thresholds. Further research should include automated or adaptive methods for determining such thresholds.

5.1. Limitations

This study has several limitations that warrant careful consideration when interpreting the findings:

- despite the application of augmentation techniques and the utilization of pre-trained models, the quantity of unique annotated images remains relatively modest, potentially constraining the generalizability to new samples;
- all images were sourced from a singular or limited number of clinical institutions, which may diminish the outcomes' interclinical generalizability;
- the study did not encompass segmentation or object detection tasks that may be critical in certain clinical contexts (e.g., precise delineation of a lesion or implant);
- Although the results exhibited commendable accuracy at a technical level, clinical validation (for instance, through a double-blind testing format involving physicians) was not conducted;
- the uncertainty thresholds and the number of MC Dropout runs were determined empirically; the development of adaptive or automatically optimized hyperparameter selection mechanisms is a direction of further research;
- the achieved level of segmentation quality (DSC = 0.837), although a significant improvement in the source-free scenario, may be insufficient for fully autonomous clinical use without the participation of an expert physician, especially in tasks where accurate boundary localization of anatomical structures is critical;
- the proposed approach is most appropriate in decision support, pre-labeling or semi-automatic analysis scenarios.

5.2. Recommendations

Aggregating images from diverse clinical environments, encompassing various device types and patients across different age demographics will enhance the models' generalizability.

Integrating the tasks of classification, segmentation, and localization of pathologies can render models more valuable for comprehensive diagnostic applications.

The implementation of activation visualization techniques (e.g., Grad-CAM, LIME) is essential to bolster clinicians' confidence in model outputs.

Engaging specialists to juxtapose model predictions with expert evaluations will facilitate the assessment of clinical accuracy and practical applicability.

Merging model outcomes with diagnostic text generation will aid in the interpretation of results within a clinical context.

6. Conclusion and Future Research Directions

The relevance of automated dental image processing is growing in light of medicine digitalization, the limited accessibility to specialists in remote areas, and the pressing necessity to speed up diagnostics. The use of deep learning, particularly pre-trained convolutional neural network models, unveils new avenues for the precise identification of dental pathologies, even in the presence of constrained data volumes. This study illustrates that the amalgamation of pre-trained models, adaptive retraining, and image augmentation culminates in high accuracy for the classification of dental conditions. The scientific novelty of this study is the demonstration of the combination of Source-Free Domain Adaptation with multi-level uncertainty estimation for segmentation of dental 3D-CBCT data. Unlike existing approaches, the proposed method provides model adaptation without access to the original domain sample, while simultaneously controlling the stability of self-learning through EMA-teacher and consistency loss. This allowed to significantly reduce segmentation errors and increase metric indicators (DSC, HD95, ASSD), which confirms the applied effect of the methodology.

The practical value of the work is that the presented approach can be integrated into clinical CAD/CAM systems and applied in scenarios where the transfer of medical data is limited or legally prohibited. The methodology increases the reliability of automatic analysis of dental images in new domains, contributing to the creation of more universal and portable medical AI systems. Thus, the work contributes to both the theoretical development of SFDA and the practical automation of clinical processes. A comparative analysis with prior research underscores the competitiveness of the proposed methodology and its capacity to generalize knowledge across complex and variable input data. Noteworthy emphasis was placed on the practicality of the chosen architectures, which are predicated on publicly accessible models, thus obviating the requirement for specialized software or hardware. The findings confirm the potential of employing pre-trained CNNs in dental diagnostics, particularly in scenarios where access to extensive annotated image datasets is limited. Future developments are envisioned to broaden the system's functionality through multi-task learning, integrating classification with segmentation. Moreover, it also provides for the integration of explanatory AI methods and the adaptation of models for application in real clinical settings with subsequent validation on independent medical samples.

Therefore, the proposed study makes a significant contribution to the existing scientific literature, as it shows for the first time that the combination of source-free domain adaptation with multi-level uncertainty assessment can not only replace traditional UDA approaches, but also provide significantly higher stability of models in the complete absence of access to the source domain. In addition, the proposed methodology details how entropy, variance and consistency learning affect the formation of pseudo-labels, which has not been previously demonstrated for dental imaging. Thus, the work significantly complements the existing knowledge, extends modern SFDA approaches to a new medical area and offers a reproducible, technically sound algorithm that can be the basis for further research.

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