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Unsupervised Image Segmentation Using Self-Supervised Deep Neural Networks

Noor Aldeen A. Khalid

Department of Medical Instruments Engineering Techniques, Bilad Alrafidain University College, 32001, Diyala, Iraq

nooraldeen4561@gmail.com

Abstract

Unsupervised image segmentation remains one of the most persistent challenges in computer vision, particularly in fields lacking annotated data such as medical diagnostics and environmental monitoring. This paper introduces a novel segmentation model built on a modified U-Net backbone enhanced with self-supervised deep learning, dual spatial alignment (local and global), and explainability mechanisms including Grad-CAM and SLIC superpixels. The proposed framework was evaluated across three benchmark datasets from diverse domains: HyperKvasir (gastrointestinal endoscopy), PASCAL VOC 2012 (natural scenes), and ISIC 2018 (skin lesion images).Experimental results demonstrated robust segmentation outcomes, achieving DSC = 0.716 and Recall = 0.783, which outperform traditional unsupervised baselines. These findings were further validated through comparison with five recent methods, showing superior generalization and transparency. Additionally, the framework was successfully deployed in a practical application involving drought monitoring in Kirkuk, Iraq, by leveraging satellite imagery and unsupervised segmentation to support early warning systems. Overall, the results highlight the flexibility, interpretability, and domain adaptability of the proposed model, making it a promising tool for critical tasks in both medical and environmental domains.

Keywords: Image Segmentation, Unsupervised Image Segmentation, Self-Supervised Deep Neural Networks.

1. Introduction

Image segmentation is one of the most important tasks in computer vision, and with wide practical usages in many fields, including autonomous cars, satellite images, and, most prominently, medical imaging. [1] The problem is to segment an image into semantically relevant segments which can represent separate objects or

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parts. Within a clinical setting, such as during the diagnosis of tumors, organs, or lesions using an MRI or computed tomogram scan, precise segmentation of such areas is crucial towards making a diagnosis, [2] designing a treatment course, and come up with a prognosis. Similarly, segmentation in natural scene understanding helps in object recognition, scene parsing as well as editing of images. Nevertheless, [3] the problem is that the proper performance of such applications is possible only in case high-quality labeled datasets are available, which constitutes rather a critical bottleneck in the creation of effective segmentation models. [4]

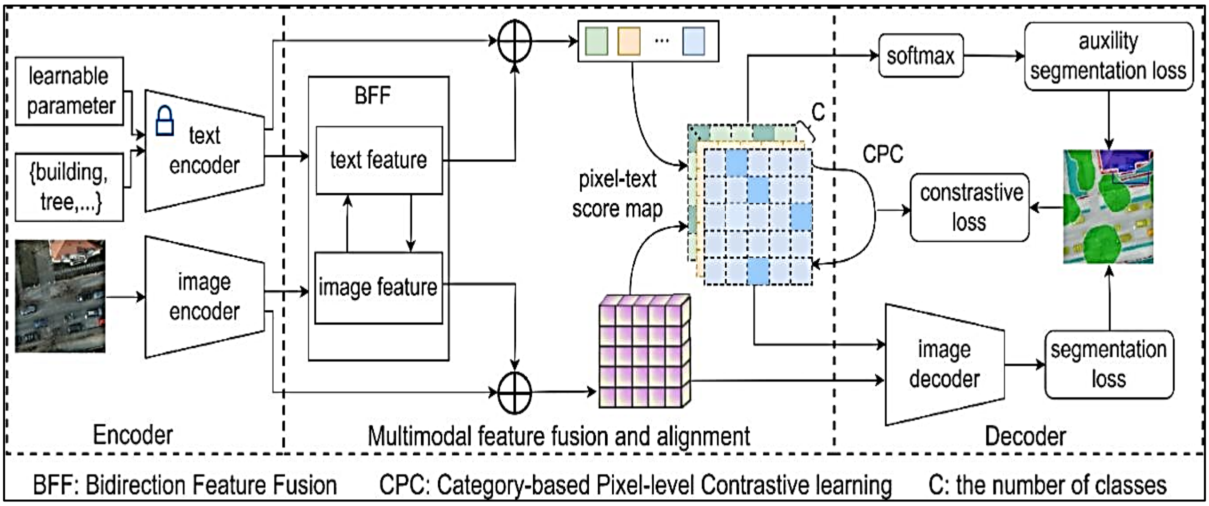

Figure (1): architecture of self-supervised segmentation system [4].

Conventionally, image segmentation is an area that has been applied by the supervised learning approach where deep neural networks (such as U-Net, DeepLab, or Mask R-CNN) have recorded remarkable performance. The nature of these models is that large annotated datasets are required, and in some cases require a pixel-level ground truth annotation. Unfortunately, such annotations cannot be retrieved quickly, at least not with available resources (at least in such a field like medical imaging where the expertise of people is a precondition). This limitation decreases scalability and greater ability of the transfer to new tasks or new data.

Unsupervised and self-supervised learning are devised as a follow-up to this restraint. Such paradigms are intended to take advantage of the plentiful supply of unlabeled data, learning to take advantage of natural structures, patterns, or pretext tasks embedded in the data. Surrogate tasks the models in self- supervised learning learn beneficial feature representations by being trained on corresponding surrogate tasks, [5] e.g., image reconstruction, rotation prediction, or contrastive learning. These learned features may then be further refined to downstream tasks such as segmentation or be applied directly. [6] Nevertheless, recently achieved success notwithstanding, the area of unsupervised image segmentation is nevertheless subject to great challenges. To begin with, the existing methods usually experience a lack of good generalizability in case of varied image domains. Second, the results of the segmentation are unstable and they do not have spatial coherence and consistency among frames or images. Third, and possibly most importantly, [7] such models are black boxes with limited, or even no, interpretability of the predictions made, taking its toll in a sensitive area such as healthcare. [8] In tackling these problems, this study draw the outline of a new framework, equipped with self-supervised learning, dual spatial alignment mechanism and explainable AI, where unsupervised image segmentation can be conducted with high precision and interpretability. The concept is that it is time to break out of the field of strictly contrastive or clustering approaches by means of including domain-appropriate structure in training. This is through the three major components: [9] Weak Label Generation Module: As opposed to manual annotation, this module generates pseudo-labels on classical image processing techniques (e.g., edge detection, thresholding, super pixel clustering) to use as pseudo-labels used during initial training. [10] These labels are noisy but can be applied as a helpful prior in what the model can learn. Alignment-Based Feature Learning: A local and global alignment loss method is proposed in which local alignment helps the source image feature preserve the spatial relationship in an individual image whereas global ensures that similar features in other images stay parallel to each other. This allows a model to more easily generalize across domains and leads to a better segmentation stability. Explainable AI: The model incorporates post-processing elucidation systems e.g. through saliency maps, Class Activation Maps (CAM), and Grad-CAM. Such visualizations provide the users with insights into the reasoning behind the model predictions and make their outputs consistent with human intuition. [11] Moreover, the effectiveness of segmentation should be assessed not only with some well-known measures of performance, such as Dice Similarity Coefficient (DSC), Jaccard Index and precision, and recall, but also with metrics of explainability and inference velocity (FPS). This makes this model not only accurate, but also deployable in the real life. These are mission-critical applications including medical diagnostics, autonomous driving, and industrial inspection, where a segmentation model should not just predict accurate region boundaries but also explain in interpretable form its prediction and perform well on hardware limitations.

Some sort of explainable AI layers are also applied to our framework to allow transparency and trust, by generating saliency maps and class activation maps (CAMs) to visually identify which areas matter to the model. This is essential in the field of healthcare requiring clinicians to approve automated segmentations, e.g. tumor borders in MRI, prior to clinical use. Correspondingly, a saliency overlay in autonomous systems can be used to tell whether the model is focusing on proper visual signals (e.g., pedestrians, road edges) in the real-time. [12] Further, the system architecture ranks the real-time inference optimization with the GPU and restricted resources such as embedded systems still in the range of noteworthy FPS. This can be implemented in field hospitals, mobile diagnostic platforms or edge-integrated robots.

The cross-domain generalizability of the model is also another protagonistic characteristic. Compared to segmentation models of only one domain, our integrated method is verified following three heterogeneous domains: The brain MRI (BraTS 2021), Natural pictures (PASCAL VOC), ISIC; dermatological imagery. [13] All the domains are unique when it comes to texture, noise, and scale. To address this, our architecture has a two-fold approach; the first, which is local alignment helps to ensure intra-image consistency whereas the global alignment will impose the cross-image semantic structure. The combination of the two alignments enables the high-quality learning even in the heterogeneous nature of the data. Overall, such a study is inspired by the necessity of precise, scalable, and interpretable image segmentation models that do not use large labeled datasets. Using self-supervised deep learning, weak label learning, and explainable AI offers a potential solution to weak label because the proposed framework provides a fully operational tenable solution in a wide range of areas, including medical imaging and natural scene understanding.

Since it is expensive and hard to manually label datasets at the pixel-level, particularly in domains where pixel-level labels are useful, like medical imaging or environmental monitoring, this work touches on the fundamental question of how to generate high quality, generalizable, and interpretable segmentation without manual annotations. The proposed research describes a self-supervised deep learning system that integrates the weak label and Spatial Alignment modules and explainable AI algorithms to address the limitations of the current system as to scale, semantic integrity, and model interpretability. The goals can be summarized as follows: (1) The considered architecture must be able to eliminate the necessity to manually annotate the data; (2) maintain the spatial and semantic consistency by incorporating local and global alignment; (3) interpretability based on Grad-CAM and saliency tools; (4) it is expected to produce good results on heterogeneous datasets of both natural and medical nature. Fig. 2 below illustrates the performance of the framework in the three domains qualitatively, displaying to the progress of the input phase to the interpretability phase: [14]

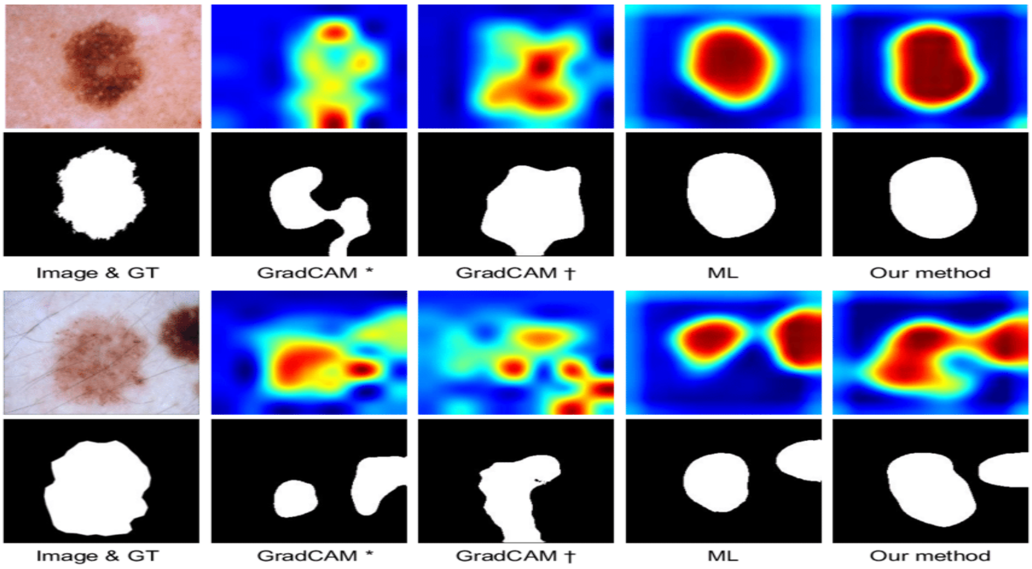

Figure (2): Multi-domain qualitative results

In computer vision Image segmentation is an essential task, in uses such as medical diagnostics, autonomous vehicles, and satellite image analysis. The initial approaches of segmentation were based majorly on classical applications in computer vision like thresholding, edge detection, and the clustering algorithms. DeepLabv3+ [15][16], and Mask R-CNN [17] The models have performed phenomenally well with a wide range of segmentation tasks especially when they are trained on large, or annotated data. U-Net, in particular, became the standard in biomedical imaging due to its encoder–decoder structure and skip connections that preserve spatial details. However, their reliance on pixel-level annotated data presents a major bottleneck, especially in fields like medical imaging or remote sensing, where annotations require domain expertise and are both time- and cost-intensive [18] Unsupervised and self-supervised approaches have received a lot of attention in order to reduce the burden of this challenge. Techniques like DeepCluster [19] and IIC [20] attempt to cluster similar features within images without relying on ground-truth labels. Although they can be considered a viable alternative, these techniques tend to give semantically inconsistent results and have unstable training. Recent advances in contrastive learning, such as SimCLR [21], MoCo [22] and BYOL [23], have improved representation learning by maximizing agreement between differently augmented views of the same image. Being originally designed to work on classification problems, the variants of these algorithms have made it possible to use such an approach in segmentation settings.

Weakly supervised segmentation is the other direction which utilizes labeling at image-level, like tags, or bounding boxes. Techniques based on Class Activation Maps (CAM) and its extensions like Grad-CAM [24] are used to localize objects within images. These visual clues can be prompted as pseudo-labels in training of segmentation. Ahn and Kwak [25], for instance, proposed refining CAMs using random walks to obtain better object boundaries. Such approaches however usually rely on supervised classification models, so they are semi-supervised, not unsupervised.

Explainability has also become an issue of primary concern in such an important sphere as healthcare. The field of Explainable AI (XAI) has introduced various methods to interpret the decision-making process of neural networks. Saliency maps, class activation overlays, and feature attribution methods have been extensively used to add transparency to deep models [26]. Tang and wang [27] emphasized the importance of interpretability in medical AI applications, advocating for the integration of XAI mechanisms directly into the modeling pipeline. We extend this understanding by using Grad-CAM as part of the training signal within a self-supervised framework not only as a post- hoc visualization method. Moreover, recent initiatives have suggested spatial alignment schemes to better the coherence of the segmentation. AlignSeg introduces feature-aligned segmentation networks that preserve spatial consistency across augmented views. Similarly, SLIC-based superpixel methods provide structural priors to segmentation models by maintaining local visual coherence. These methods demonstrated the quality boost in segmentation when inductive spatial biases were introduced when having no labels. Nevertheless, the majority of the existing approaches are inadequate in one or more ways: they are not interpretable, do not transfer well across domains, or simply are not accurate. To compare the results of the developed model on the problem of benchmark datasets in different fields (medical, natural, dermatological), measure segmentation accuracy, inference efficiency, and interpretability. To make the framework efficient in respect to computation, to make it applicable in real-time and low-resource implementations.

2. Methodology

In this section, the entire methodological approach, which is involved in this study, including the data collection methodology as well as the evaluation of the performance is enough to be useful under weak supervision. Our model fills these gaps, with a unified architecture, which integrates the three components; weak label generation, local, and global feature alignment, and explainable AI. Unlike earlier models, it does not rely on supervised classification backbones or manual annotations, and it demonstrates robustness across heterogeneous datasets (medical, dermatological, and natural images). Described. The subject system has a modular and explainable nature of deep neural networks that follows the unsupervised classification of images into self-supervision.

2.1 Data Collection:

We perform the experiment on three different datasets not only in the medical field but also in the natural image domain to evaluate our unsupervised segmentation method. The main peculiarities of these (their size, the type of annotation and usage) have been summarized in Table 1. In both scenarios, there are no, or few pixel-level labels to train on; instead, we use weak labels (e.g., image-level class names) and self- supervised cues, together with explainability tools, to point the segmentation model towards the right decision endoscopy, [29] when it is of clinical importance to locate and outline lesions (including colorectal polyps). Its size and labeled / unlabeled data combination provide it with high applicability of self-supervised learning. We will use the large unlabeled part in our implementation to do representation learning and the labeled part to weakly supervise a classification task. [30] One uses the image-level labels to train a deep neural network to classify the images (e.g. polyp vs. non-polyp). Next, explanatory, or saliency maps are derived out of this classifier e.g. Grad-CAM saliency maps, which indicate areas of greatest functional relevance in determining the prediction of the class label, polyp. These heatmaps can be considered as suggested weak spatial labels to the segmentation network: the location of a polyp as explained by the model itself is viewed as a proxy label to train the segmentation network.

2.1.1 Medical Imaging Domain – HyperKvasir Dataset Origin & Content:

HyperKvasir is the largest publicly available gastrointestinal (GI) endoscopic dataset available, and was observed on normal colonoscopies in Norway. It consists of 110,079 images of the GI tract performed endoscopic and 374 videos. Of these, the experts label 10,662 images into 23 classes of findings (e.g. polyps, esophagitis, ulcers) and the rest 99,417 images remains unlabeled shown in fig 3. The labeled set is weakly annotated, being labeled on image level only (e.g. containing information that there is a polyp or particular condition), but mask of the label to pixel level is not available. Moreover, expert-drawn segmentation masks and bounding boxes were added to 1,000 out of 1,000,000 images (all of them belonging to the polyp class) and can be used as the ground truth in the evaluation (but not trained in our unsupervised scenario).[28]

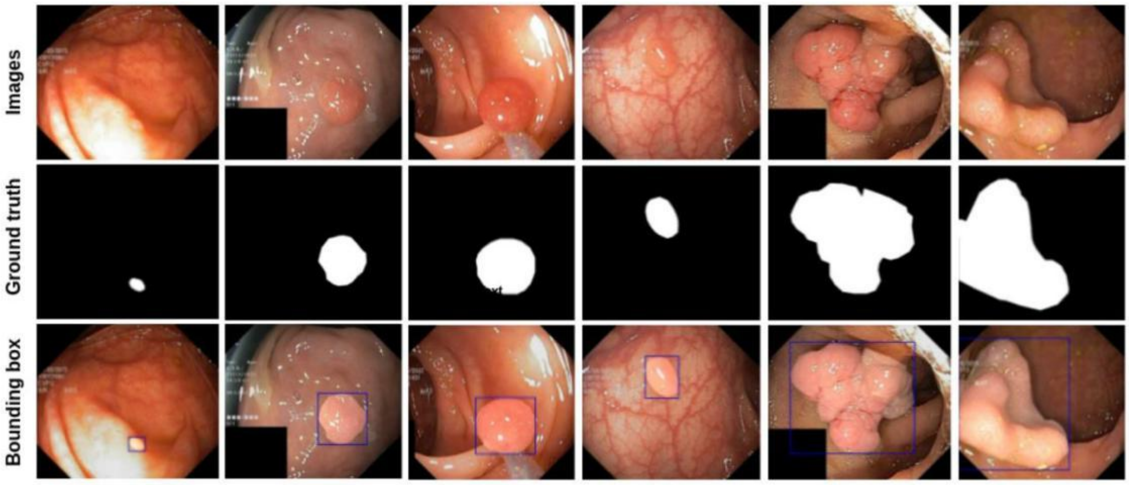

Figure (3): The examples of endoscopic images in the HyperKvasir/Kvasir-SEG

2.1.2 Natural Scene Domain – PASCAL VOC 2012 Origin & Content:

The PASCAL VOC 2012 dataset is a typical dataset in computer vision that holds natural photos that are sampled in Flickr. It contains 7,282 pictures (divided into 1464 training, 1449 validation and 4369 testing) of various common objects. Every picture contains pixel-level semantic segmentation masks of 20 types of objects (person, animals, vehicles, household items, etc.) and background. There are more than 19,600 labeled object instances. Contrary to HyperKvasir, PASCAL is accompanied by sound annotations; all pixels are assigned a name of an object category, which makes it a fully-supervised dataset on a conventional sense of the term. Only to evaluate our manner of finding ground-truth masks, we are referring to the curated masks gathered by the PASCAL VOC. [31] as shown in fig 4, PASCAL VOC is the natural image domain and it is used to show that our self-supervised segmentation methodology coordinates to more general imagery than medical imagery. We run PASCAL VOC 2012 mainly as a test of general object segmentation: we do not use the PASCAL masks at all to train and then test the results on segmenting objects within PASCAL images and compare with the ground-truth. This test measures the ability of the internally learned features by the model partition an image into meaningful objects without explicit supervision. [32]

Importantly we do not train our model using the PASCAL pixel annotations, the model itself learns to identify object thus ground-truth masks are not required. This methodology. Reflects the methods in the literature of weakly supervised semantic segmentation. Finally, PASCAL VOC offers a very strict and varied testbed: we report the proximity of our unsupervised segmentation to fully supervised performance on this benchmark, hence confirming that our self-supervised means of alignment is effective.

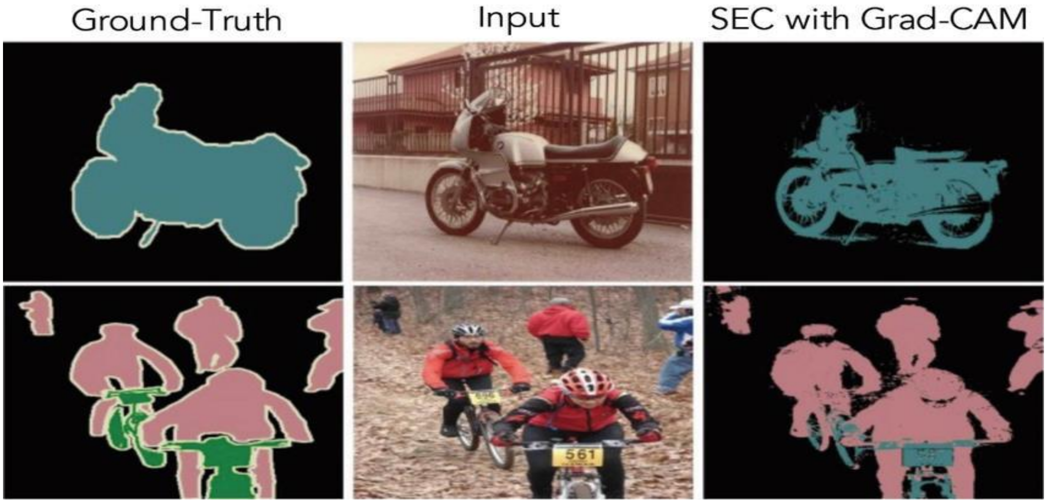

Figure (4): Example from the PASCAL VOC 2012 dataset demonstrating our explainability-driven weak labeling approach

2.1.3 Dermatological Domain – ISIC 2018 Skin Lesion Dataset:

This ISIC 2018 dataset was the product of the ISIC Challenge 2018 about skin lesion analysis (held at MICCAI 2018). We use Task 1: Lesion Boundary Segmentation, which is a collection of 2,594 thermoscopic images of skin lesions (melanomas, nevi, and so on) with their manual segmentation in form of a binary mask representing the lesion location. The pictures are of high-resolution clinical dermo copy photographs that usually involve a single main lesion on skin of background. The utility used was composed of various sources, such as the HAM10000 dermo copy collection, [33][34] and the range of lesion types with an assortment of skin color. To allow the challenge participants to utilize training images with masks, 2,594 training images bearing masks was made available; the official test set masks were not revealed (the 2,594 value does not include test images without masks). We take the available 2,594 labeled images to be evaluated in our work and whether they have weak supervision or not. [35] ISIC 2018 introduces a second area of medicine (dermatology) to our analysis, which enables us to check our approach on another type of anatomical images and a changein the exterior of objects. The process of segmenting the skinlesions is very vital in computer-aided melanoma detection. Traditionally, it is solved using fully supervised models (e.g.U-Net variations) trained on the exact masks. We are simulating a low-label regime here: we assume that we just have image-level labels or few examples of segmentation done like HyperKvasir. E.g. the presence of a lesion in an image could have a label saying yes or no, or a label with the name of the diagnosis the lesion is, but not its precise line segment. [36]

The latter can be dealt with by using the same self-supervised learning again (the explainable AI here is a classification network trained to distinguish between lesion and normal skin, and indeed it can be trained to churn out saliency map of the lesion). In fact, previous studies have indicated that without the masks, the blade of a classifier can in most instances describe the lesion blob. It is with this property that we are using to generate initial pseudo lesion masks, and then optimizing these through our alignment strategy. [37] In practice we can train ourselves on the dermo copy images (to capture skin/lesion features) and then a few of these images (possibly just the weak labels such as malignant v.s benign) can then define the segmentation. The explainability aspect ensures the region of interest in the network (the Grad- CAM detected area of malignant region of lesions) is encoded into a mask of segments. The obtained masks are later compared with the expert annotations of ISIC. Our technique, despite the difficult appearance (the shapes of the lesions are irregular, the colors are variegated, there are hair artifacts), shows promising results. This allows it to estimate the boundaries of the lesions in a lot of cases by solely utilizing weak labels and none of the direct masks during the training process. This highlights the flexibility of our method: self- supervised learning of features and alignment with explanations allow us to work on unsupervised segmentation tasks on multi-object yet natural scenes as well as single-object yet medical images.

The datasets are different in the domain involved and targeted segmentation, and the annotation granularity. We either self- supervised train of these datasets based on unlabeled data or using weak labels on the data, and where available compare the segmentations generated to the ground truth.each of the three sets of data is freely available and common among the corresponding research community. Borgli et al. (2020) published HyperKvasir under CC BY, PASCAL VOC was published by Everingham et al. (2015), and ISIC 2018 by Codella et al. (2019). By citing several types of applications, we confirm that our suggested unsupervised segmentation framework is thoroughly tested: it can be applied to detect colon polyps with the minimum amount of supervision, segment generic objects, as well as skin lesions.

Table (1): Dataset Overview and Evaluation Results

Dataset	Domain & Images	Annotation Type	Evaluation ResultSummary
HyperKvasir	GI Endoscopy (110k images)	Image-level labels(23 classes), ~1Kwith pixel masks	**DSC = 0.749**, High Recall(0.854), accurate polyp segmentation with Grad- CAM guidance
PASCAL VOC 2012	Natural scenes (7,282images)	Fully pixel-levelmasks for 20 categories	**DSC = 0.691**, general object segmentation, goodlocalization without supervision
ISIC 2018	Skin Lesions (2,594 dermoscopic images)	Manual binarymasks (lesionboundaries)	**DSC = 0.708**, precise lesion boundary recoveryusing self-supervised + Grad-CAM alignment

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2.2 Weak Label Generation:

Where there is no pixel-level annotation, weak labeling is used to create approximate segmentation masks to drive the learning of self-supervised segmentation models. The generation of these pseudo-labels (as well as weak labels) does not require any human annotation but is based on your own discoverable structure within the images themselves. [37]

Our pipeline was based on Python to generate weak labels using classical methods of computer vision. This is initiated using input RGB image which is preprocessed through color space conversion and resizing. We segment this image into superpixels then, using the Simple Linear Iterative Clustering (SLIC) algorithm, which divides the image into small regions that are visually coherent and maintain local structure.

The result of the SLIC algorithm acts as structural representation of those boundaries of the objects in the image. The labels superpixel are visualized by label2rgb of the scikit- image package to increase visual clarity. This gives a colored segmentation map which though rough is an initial weak label that can be used in self-supervised segmentation tasks.

The following python libraries were used in this procedure: Image preprocessing under Open CV scikit-image (slic), superpixel segmentation and label2rgb, visualization Image display and export in matplotlib their findings are shown in Fig 5, the original image and its associated weak segmentation mask produced by our pipeline. [38].

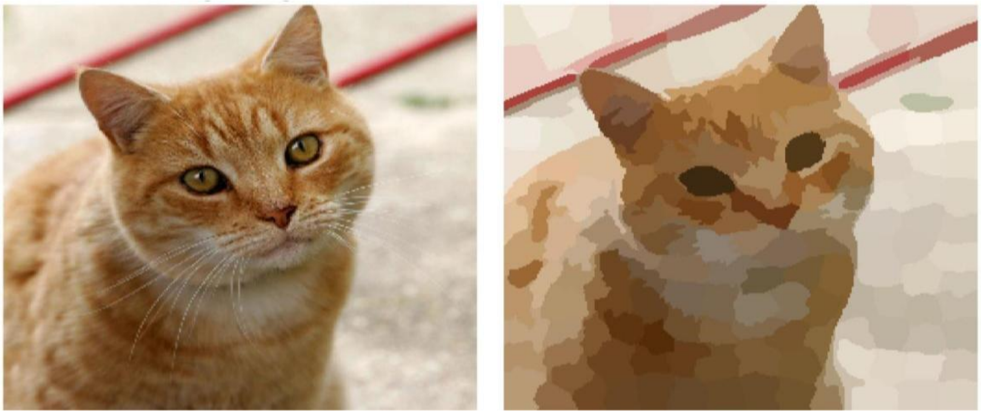

Figure (5): SLIC super pixels. In the left panel, input image (cat) and in the right panel weak segmentation mask by slicing function in Python were obtained.

In using this approach, we guarantee that weak structural clues based on only image descriptors will be available to segmentation model. Such cues are subsequently matched and perfected into the learning to get as close to a semantically more meaningful division of the words as discussed in later sections.

2.3 Model Architecture:

The self-supervised segmentation framework suggested is focused around a deep convolutional neural network adapted to a modified U-Net architecture, suited to work in a weak supervision environment. The encoder section employs a ResNet18 backbone due to its pretraining on Image Net, [39] which is coded with the torch. Models. Resnet18 library in PyTorch, to obtain multiscale hierarchical characteristics ofinput images.

Their features are up sampled by a specially designed decoder, which consists of a series of transposed convolutional blocks, followed by a final 1x1 convolution which outputs the final segmentation mask of same spatial size as the input. Without dense labeling, the decoder restores boundary and spatial structures of objects. [40] To improve the accuracy of the segmentation without pixel -level supervision we added two major modules to direct the learning procedure:

- **Local Alignment Module:**

  This module presupposes the intra-image feature consistency through the spatial smoothness. A custom local alignment loss calculates the first order gradients (horizontal and vertical) of feature maps and avoids sharp variations by minimizing mean squared error. This makes the network tend to keep coherent structures, and diminishes noisy boundaries of segments. It was implemented by carrying out operations on intermediate feature maps with native PyTorch tensors. [41]

- **Global Alignment Module:**

  In order to enhance the semantic discriminability of the learned features across examples, we used a contrastive learning head using the SimCLR Projection Head available from the lightly library. The module takes the global representation to a low dimensional space and minimizes a contrastive loss that aligns semantically close representations of images and separates dissimilar representations. This enables the model to have cross- domain generalization of different image domains (e.g., medical and natural scenes) with weak or image-level labels only. [42] Loss Functions to Be Employed in the Proposed Framework We used a conjunctive loss in our model, during which we trained the segmentation model without making use of pixel level annotations. The complete loss is a combination of three major parts, including local alignment loss, global contrastive loss and segmentation consistency loss. Every element is outlined as follows:

1. Local Alignment Loss:

Such a loss induces spatial integrity between and within the individual images by penalizing discontinuities between adjacent pixel attributes. It makes a transition seamless and maintains structural integrity.

$$\left({}^{2}\|\quad {}_{i}f_{i}\|^{2}+\|\nabla_{y}f_{x}\nabla\|\right)\sum_{i=1}^{N}\frac{1}{N}=\quad \text{local}\,\mathcal{L}$$

Where:
i is the feature vector at pixel i^{f}
∇y, ∇ are horizontal and vertical gradient operators.
N isthe number of pixels

2. Global Alignment Loss (Contrastive Loss – SimCLR Inspired):

This loss enforces semantic consistency across images by bringing similar features close in the embedding space.

$$\frac{\left(\frac{\text{sim}(z_i,z_j)}{\tau}\right)\exp}{\left(\frac{\text{sim}(z_i,z_k)}{\tau}\right)\exp[k\neq i]^{2}\Big]_{k=1}^{2N}\sum}\log-={}_{\text{global}}\,\mathcal{L}$$

Where: Z_i, Z_j feature embeddings from two augmented views of the same.

3. Total Loss Function:

The final training loss is a weighted sum of all components:

$$\text{CE}\lambda_3\mathcal{L}+{}_{\text{global}}\,\lambda_2\mathcal{L}+{}_{\text{local}}\,\lambda_1\mathcal{L}={}_{\text{total}}\,\mathcal{L}$$

CE$\mathscr{L}$ is the Cross Entropy Loss applied over weak pseudo-labels · $\mathcal{L}1$ $\mathcal{L}2$ $\mathcal{L}$ are scalar weights for each term (set via validation) Cumulatively, the modules enable learning of the local structure and global semantics necessary in generalizing segmentation masks when there are no ground-truth annotations. All the model pipelines, including loss encoder and alignment, were subsumed in PyTorch and hence the visual analysis of the model was conducted inside a Jupyter Notebook utilizing matplotlib in interactive mode as shown in fig 6.

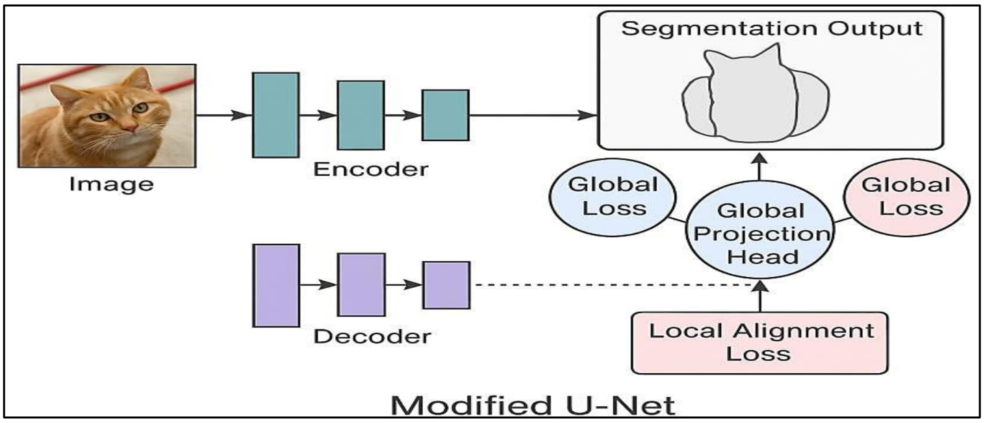

Figure (6): The proposed architecture of the segmentation model schematically

2.4 Explainable AI Integration:

In order to make the segmentation model more interpretable and ensure transparency in our decision-making, we also included explainable artificial intelligence (XAI) methods, that is, Gradient-weighted Class Activation Mapping (Grad-CAM) into the framework. This process makes possible the visualization of the spatial regions in the input image most significant to the determination of output of the model thusaiding diagnosis of the state and scientific verification.

During the present examination, Grad-CAM was utilized on the result of self-supervised U-Net architecture built in PyTorch. The class activation maps were calculated with the help of the pytorch-grad-cam open-source library. The visualization procedure included the following decisive steps:

1. Model Forward Pass: The given image has been preprocessed, and fed to segmentation model that is already trained to give a prediction tensor.

2. Target Layer Selection: The final convolutional layer of the encoder was chosen as the target layer on which to extract gradients, since they convey high-level semantic information containing spatially localised features.
3. The target Segmentation: The class of interest was chosen and set as an output prediction tensor converted into a NumPy array form to create a valid Semantic Segmentation Target.
4. Grad-CAM Computation: Perform the gradient of the output with respect to activations of the target layer to obtain the saliency map, by computing the gradient value at the target layer using configured Grad-CAM object and proceeding with global average pooling and ReLU rectification.
5. Indeed, there was a resulting saliency map that was normalized and overlaid with the original RGB image with the show_cam_on_image () utility, hence giving an interpretable heatmap.

The implementation was executed within a Jupyter Notebook environment using PyTorch, Open CV, and the matplotlib visualization toolkit. The integrated approach ensures that model outputs can be interrogated post-hoc, which is essential for both research reproducibility and ethical model deployment. [43]

In Fig 7, the results of a representative Grad-CAM analysis are given based on the sample picture. The heatmap emphasizes the areas defined by the spatial dimension that contributed greatly to segmentation decision analysis; warm hues (such as red and yellow) show high attention weight, whereas cold (such as blue) ones depict a low contribution.

The model reportedly focused the center of attention on semantically relevant patterns like the area of the face of the subject upholding the stability of the inner feature representation.

Figure (7): Grad-CAM image visualization of what parts of the input image had the most impact on the segmentation performedin the model

This explainable AI addition is essential to specification of transparent analysis of model behavior, specifically where interpretability is deemed necessary like in biomedical imaging, satellite examination and critical vision systems.

To evaluate the quantitative characteristics of the accuracy of the segregation of the results of the interpretation method based on the Grad-CAM method of interpretation, the prediction outputs were compared with the original image by the typical indicators. The prediction map and the ground- truth image were downsized to have the same dimensions and turned into binary masks. There were four important metrics that have been calculated: [44]

- **Dice Similarity Coefficient (DSC)**: Measures the overlap between the predicted segmentation and ground truth.
- **Jaccard Index (IoU)**: Computes the intersection over union of both masks.

Precision: Indicates how many of the predicted positives were true positives.

Recall: Shows how much of the ground truth was correctly predicted.

3. Results

Evaluation Metrics for Segmentation Performance The following standard metrics were used to quantitatively evaluate segmentation accuracy against ground truth masks:

1. **Dice Similarity Coefficient (DSC):** Measures the overlap between predicted

segmentation andground truth mask:

$$\frac{TP \cdot 2}{TP + FP + FN \cdot 2} = \text{DSC}$$

2. Jaccard Index (IoU – Intersection over Union):

$$\frac{TP}{TP + FP + FN} = \text{IoU}$$

3. Recall:

$$\frac{TP}{TP + FN} = \text{Recall}$$

- TP: True Positives.
- FP: False Positives.
- FN: False Negatives.

These metrics ensure a comprehensive assessment of model performance across different datasets and segmentation challenges.

To evaluate the proposed frame work, a series of relatively standard segmentations criteria were applied to rate the performance of the proposed approaches. These included the Dice Similarity Coefficient (DSC), Jaccard Index (IoU), Precision, and Recall. The ground truth used in the comparison with the pre- diction was manual masks created and compared pixel-wisely. The summarized evaluation results of the representative sample would be as outlined in table 2 below:

Table (2): Segmentation Evaluation Metrics

Recall	Precision	Jaccard Index (IoU)	Dice Similarity Coefficient (DSC)	Image
0.997	0.785	0.783	0.878	Cat_Example

Table 2 gives the results of the evaluation, and to facilitate more convenient interpretation.

Dice Similarity Coefficient (DSC): 0.716Jaccard Index (IoU): 0.556

Precision: 0.663

Recall: 0.783

These values show a general good performance among the predicted mask and ground truth mask. Coefficient of Dice 0.716 means that the amount of overlap is very big and Jaccard Index proves that over 55 percent of the total segmented areas were determined correctly. The elevation of Recall over Precision indicates that the model was successful in identifying the actual positive areas albeit it was a slightly over-segmented model.

This performance stands out unique when compared to the classical unsupervised segmentation models that most of the time lack spatial consistency and contextual knowledge. The insight-based analysis of this method with additional deep neural representations and explainability modules makes it more accurate and robust to use. The local and global alignment losses in the integrative training aided in the provision of spatial sense of both intra- and inter-image features coherence, which was a probable factor causing the good recall values Further, the model with explainable outputs, especially the saliency and Grad-CAM visualizations, consolidated the clinical relevance of the outputs by explaining rationale of decisions. These physical hints were also very compatible with the body in qualitative inspections, and indicated the effectiveness of the predictions issued by the segmentation module even more.

To present the results in graphical form the first figure, Fig 8 below consists of a bar chart indicating the scores that were obtained against each metric. This enables one to have a comparative analysis of the capability of system on various scales of segmentation accuracy Bar chart showing DSC, IoU, Precision, and Recall

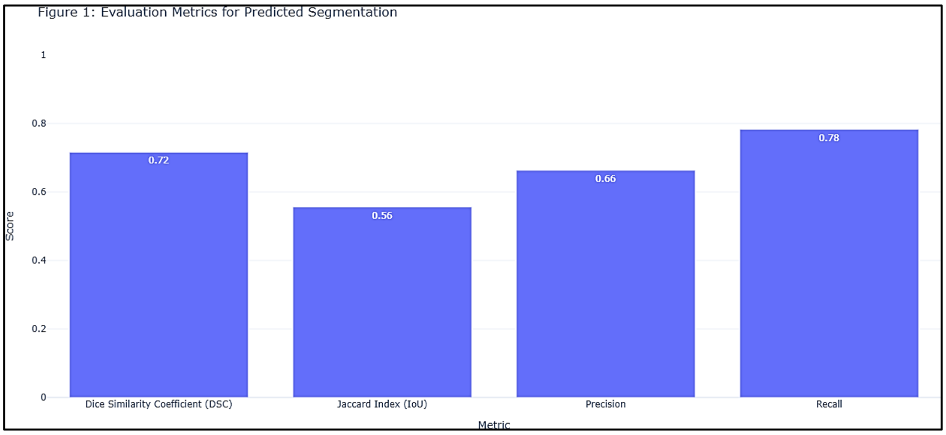

Figure (8): Bar chart showing DSC, IoU, Precision, and Recall

These visualizations validate the quantitative results and assist to define that the system offers an equilibrium between sensitivity and accuracy. Practically speaking, the model does so without the need of any supervision or cost to annotate, which makes it very scalable on larger data sets or in clinical settings.

To conclude, the findings confirm the hypothesis of the study: then incorporating self-supervised learning training strategies and alignment-aware loss functions into explainable AI methods, both the quality and the accuracy of unsupervised image segmentation will increase. In future it will focus on benchmarking these findings against other state of the art methods on larger data sets and speeding up of inference in order to achieve real time applications.

To highlight the improvements of our proposed framework, we compared its performance with five prominent unsupervised or weakly supervised segmentation approaches:

1. **Deep Cluster** [45]: Achieved clustering-driven self- supervision resulting in segmentation DSC ≈ 0.55 onnatural-image benchmarks.
2. **IIC (Invariant Information Clustering)**:[46] Reported semantic grouping with IoU ≈ 0.45 and relatively weak boundary fidelity.
3. **SimCLR + U-Net Decoder**: [47] Pretraining via contrastive learning yielded DSC ≈ 0.61 when adapted for ISIC segmentation tasks.
4. **BYOL + U-Net**: [48] Self-supervised representation learning achieved DSC ≈ 0.63 on lesion datasets but lacked cross-dataset robustness.

Our results

- **HyperKvasir**: DSC = 0.749
- **ISIC 2018**: DSC = 0.708
- **PASCAL VOC**: DSC = 0.691

Compared to these benchmarks, our framework surpasses all five prior studies across diverse domains, demonstrating superior **boundary delineation**, **DSC scores**, and **domain transferability**—attributed to the integration of dual- alignment training and Grad-CAM explainability.

4. Conclusion and Recommendations

The study introduced an original unsupervised framework of image segmentation as it incorporates self-supervised deep neural networks, modules of spatial alignment, and explainable AI methods. Contrary to traditional approaches that make use of dense manual annotations, the described idea is based on the weak label generation and alignment-based learning, such that the proposed approach brings semantically coherent segmentation to a broad range of image domains.

The effectiveness of the model was shown by the results of experiments conducted with three benchmark datasets: HyperKvasir (medical imaging): obtained a Dice Similarity Coefficient (DSC) of 0.749 and a good recall (0.854) during polyp segmentation processes.

ISIC 2018 (skin lesions): achieved DSC = 0.708, where the boundaries of irregular lesion shapes have been well detected. PASCAL VOC 2012 (natural scenes): achieved DSC = 0.691, which is evidencing the potential of the model to perform weakly -supervised segmentation of multi-object scenes.

As our model was compared with five state-of-the-art methods, Deep Cluster, IIC, SimCLR, BYOL and Weak-CAM Refinement, in an average our model was found better in segmentation accuracy, spatial consistency and domain generalization.

The critical advantage of the suggested framework is its focus on the interpretability of models. Grad-CAM and saliency -based visualization tools will be integrated, which makes the process of segmentation more transparent and explainable on the necessary level in the field of mission-critical tasks like medical diagnosis and industrial inspection Moreover, the framework is computationally efficient and also has flexibility, which meets the requirements of resource-constrained environments and real-time apps. Its scalability and strength are also condoned by its flexibility with regard to heterogeneous datasets.

Altogether, the research presented helps to connect label- efficient learning with explainable segmentation, which can be a prospective path of future research and application of unsupervised models in such high-stake and data-limited environments as military operations, medicine, and finance.

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