University of Münster
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Salient Object Detection for Social Media Images

Seminar Thesis

in the context of the seminar

More than meets the A-eye: Reflecting Human Vision in Artificial Intelligence

submitted by

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0.1 Introduction

The topic of image segmentation is a field of interest in computer vision since the 1970s and remains highly relevant to this day. Recent advances in segmentation models enable point-based, zero-shot segmentation. By combining real eye-tracking data with such a model, we aim to create a practical approach for salient object detection for social media images that reflects actual human visual behaviour. Using gaze data directly as prompts, we aim to derive data-driven object masks that represent what was looked at most. Beyond developing a segmentation pipeline, we are motivated to illustrate what kinds of insights become possible once salient objects in those social media images can be reliably extracted.

In existing literature, salient object detection has been implemented for specific use cases, but not within the social media context with its highly diverse and complex content. Therefore, research has not yet investigated what could be done with extracted salient objects in the social media context. Our work aims to provide an initial exploration of the research gap between social media, real human gaze behaviour and salient object detection.

0.2 Theoretical Background

0.2.1 Image Segmentation

Image segmentation is the process of dividing an image into different regions by grouping pixels and assigning each pixel a label. This step is an important part of many computer vision applications, such as detecting tumors in medical images or identifying pedestrians in autonomous driving. According to human visual perception, the identified regions are non-overlapping and meaningful - however, defining what exactly counts as a "meaningful" region can be difficult, as human perception is subjective and object boundaries are not always clear (Yu et al., 2023).

There are three common types of segmentation: *Semantic segmentation* assigns every pixel in an image a semantic label, such as "car" or "sky". *Instance segmentation* separates individual objects within the same class, for example distinguishing several people in one image. *Panoptic segmentation* combines both approaches by providing pixel-wise class labels and also identifying individual object instances.

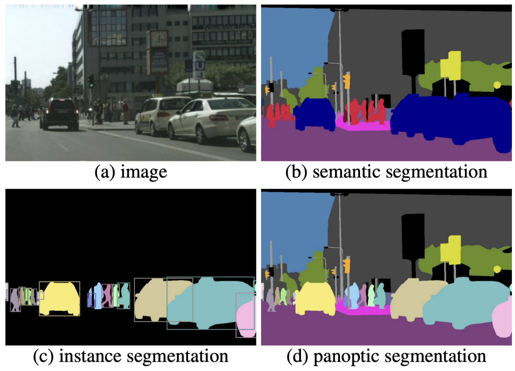


Figure 1 Types of image segmentation by Kirillov et al., 2019

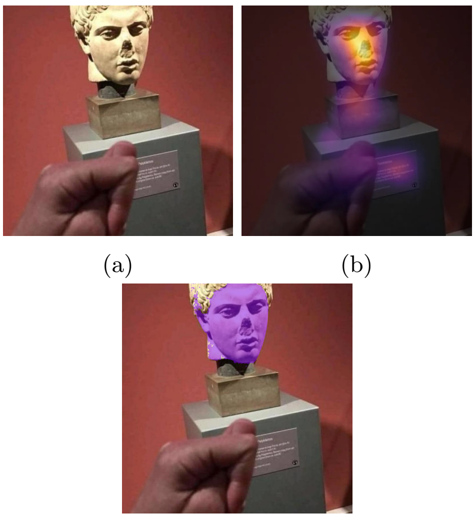
Earlier approaches to image segmentation include algorithms such as k-means-clustering (Dhanachandra et al., 2015). Yet in recent years, deep learning models have significantly improved the segmentation effect and performance, therefore becoming the dominant method for solving segmentation tasks in complex environments (Minaee et al., 2022).

According to Zhou et al. (2024), the above-described image segmentation methods fall into the category of generic image segmentation (GIS). The category of promptable image segmentation (PIS) extends GIS by specifying the target to segment through a prompt. This prompt can have various forms such as text, box or points.

0.2.2 Salient Object Detection

The human visual system pays more attention to certain parts in an image, a property known as saliency. Inspired by this mechanism, *saliency detection* models aim to predict which regions in an image are most likely to attract human visual attention. These models typically provide saliency maps in form of heat maps, in which higher intensity values indicate regions detected to be more important (Ahmadi et al., 2018).

Salient Object Detection (SOD) – also referred to as salient object segmentation (Borji et al., 2019) or saliency segmentation (Kakanopas & Woraratpanya, 2021) – goes one step further by segmenting the most salient object(s) of an image. SOD can be interpreted as a two-stage process: 1) Detection of the most salient object and 2) Accurate segmentation of the region of that object. In contrast to general image segmentation, SOD focuses on segmenting only those objects that are (or that are predicted to be) most salient (Borji et al., 2019; T. Liu et al., 2011). Figure 2 illustrates the difference between saliency detection and salient object detection.



(a) (b) (c)

Figure 2 (a) the original image, (b) saliency map (Alexander Kroner, 2025) and (c) salient object detection mask generated using SAM3 guided by the eye-tracking data

0.2.3 Image Segmentation Models

Table 1 offers a structured overview of prominent and state-of-the-art image segmentation models, organized according to the segmentation tasks for which they are most suitable.

For our use case, only promptable segmentation models are suitable, as the eye-tracking data provides point inputs that will be used to implement SOD. Among the identified promptable models, SAM and its successors are the only widely adopted models that natively support point-based prompts (Kirillov et al., 2023). In contrast, Grounded-SAM (Ren et al., 2024) and Florence-2 (Xiao et al., 2023) are limited to text prompts, and SEEM, whose last update dates back to 2023, is less actively maintained and less commonly used than SAM (Zou et al., 2023).

The Segment Anything Model (SAM) was developed by Meta AI and first introduced in mid-2023 (Kirillov et al., 2023). SAM performs object segmentation based on prompts, including points and bounding boxes. With more than 15,000 citations, SAM has become one of the de facto standards for domain-specific applications and is already employed in several specialized salient object detection settings, such as camouflage object segmentation and medical image segmentation (T. Chen et al., 2025), RGB-T SOD (Z. Liu et al., 2025), and text-driven SOD (Yuan et al., 2026). The most recent version, SAM 3, was released on 19 November 2025. Its rapid adoption - reaching over 5.3k GitHub stars within two weeks - indicates strong community interest (Meta Research, 2025) . Compared to previous versions, SAM 3 introduces the ability to detect and segment instances that match a given text description, and to further refine detections using visual examples (Carion et al., 2025).

Generic Image Segmentation		
Instance segmentation	**Semantic segmentation**	**Panoptic seg tation**
Mask R-CNN He et al., 2018	DeepLabV3 L.-C. Chen et al., 2017	Mask2Former Cheng et al., 2022
YOLOv11-seg Ultralytics, 2025	FCN Long et al., 2015	Panoptic FPN Kirillov et al., 2019
YOLACT Bolya et al., 2019	U-Net	Mask DINO Li et al., 2022
Mask2Former Cheng et al., 2022	SegFormer Xie et al., 2021	...
...	...	

Table 1 Overview of prominent image segmentation models categorized by segmentation task.

0.2.4 Evaluation of Image Segmentation Models

When evaluating image segmentation models, a distinction can be made between subjective and objective methods. Subjective evaluation involves a human assessing the quality of the segmentation results. Although this approach is convenient, the judgement may vary significantly between evaluators (Wang et al., 2020). Objective evaluation methods typically rely on comparing ground truth masks with the masks generated by the model on a pixel-based level. A commonly used metric is Intersection over Union (IoU), which measures the overlap between the prediction and the ground truth (e.g. Kirillov et al., 2023). Metrics commonly used in salient object detection include the F-measure, Precision-Recall and the Mean Absolute Error (MAE) (Borji et al., 2019).

0.3 Methodology

0.3.1 Experimental Design

Our prototype implements a pipeline that transforms raw eye-tracking data into semantically meaningful object segmentations. The approach is motivated by the hypothesis that human visual attention, as captured through fixations, provides a reliable signal for identifying salient objects in social media images. The pipeline consists of four main stages: First, we extract fixations from the raw 60 Hz eye-tracking measurements to obtain stable representations of visual attention. Second, we apply DBSCAN clustering to group spatially proximate fixations, identifying distinct regions of interest regardless of their shape. Third, we compute duration-weighted centroid points for each cluster to serve as location estimates for salient objects. Finally, we use these saliency points as prompts for SAM3, a state-of-the-art segmentation model, to extract precise object boundaries. This design leverages actual human visual behavior rather than computational saliency predictions, potentially offering more ecologically valid results for salient object detection in real-world social media contexts.

Fixation Extraction. The raw eye-tracking data consists of gaze position measurements recorded at 60 Hz, capturing where participants looked throughout their viewing session. However, these high-frequency measurements contain substantial noise from micro-saccades, measurement errors, and brief involuntary eye movements. To obtain a more meaningful representation of visual attention, we extract fixations, which are stable periods where gaze remains on a specific location. Fixations represent deliberate visual processing rather than transitional eye movements, making them a more appropriate input for identifying salient regions. This preprocessing step effectively filters noise while preserving the spatial and temporal characteristics of participant attention.

Fixation Clustering. Having extracted stable fixation points, we next identify spatially coherent regions of attention, we apply DBSCAN

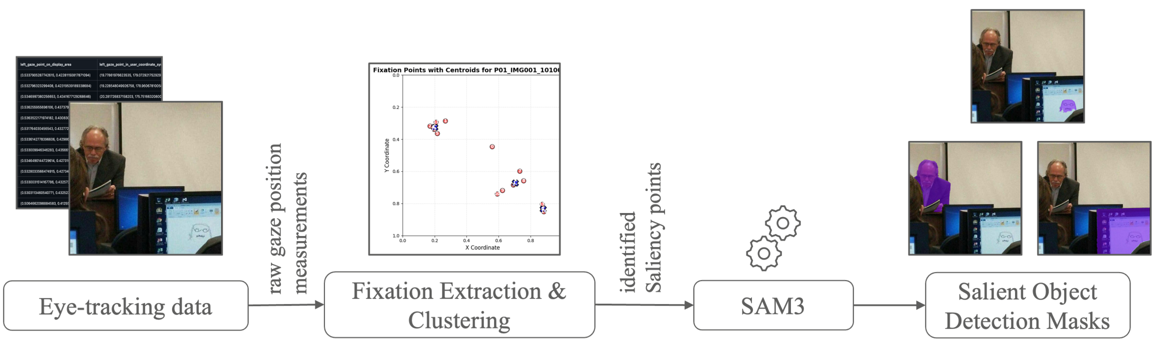


Figure 3 Overview of our proposed prototype for saliency object detection using the eye-tracking data and SAM3.

(Density-Based Spatial Clustering of Applications with Noise) to group spatially proximate fixations. DBSCAN is particularly well-suited for this task because it can discover clusters of arbitrary shape without requiring a predetermined number of clusters. This flexibility is crucial for social media images, where salient objects vary considerably in size, shape, and spatial distribution. Unlike centroid-based clustering methods such as k-means, DBSCAN can effectively capture elongated or irregularly shaped attention patterns that may correspond to complex objects or multiple nearby objects of interest. Additionally, DBSCAN's noise detection mechanism allows us to distinguish between sustained attention on specific regions and scattered, less meaningful fixations (Ester et al., 1996).

Saliency Point Generation. From the clustered fixations, we generate point-based location estimates to represent salient regions in the image. We consider two sources for these saliency points: first, all clusters identified by DBSCAN, and second, noise points (fixations not assigned to any cluster) that exceed a fixation duration threshold of 1 second. This threshold ensures that even isolated but sustained attention is captured as potentially salient, though we acknowledge this value is preliminary and may require adjustment based on empirical evaluation. For each cluster, we compute a duration weighted centroid, where the position of each fixation is weighted by how long participants attended to that location. This weighting scheme ensures that areas receiving more sustained attention exert greater influence on the final saliency point position, better reflecting the perceived importance of different regions within a cluster. While this centroid-based approach provides a single representative point per salient region, it does sacrifice information about the spatial extent and shape of the attention distribution, which may be relevant for irregularly shaped objects or diffuse attention patterns.

Object Segmentation. To extract precise object boundaries from the identified saliency points, we employ SAM3 (Segment Anything Model 3), a state-of-the-art segmentation model that supports prompt-based inference (Carion et al., 2025). The choice of SAM3 is motivated by two key requirements: first, the need for high-quality segmentation performance comparable to current best practices in the field, and second, the ability to accept point prompts that guide the segmentation process. SAM3's architecture is specifically designed for promptable segmentation tasks, making it well-suited for our zero-shot approach where saliency points serve as spatial prompts indicating regions of interest. By providing our computed saliency points as input prompts, SAM3 generates segmentation masks that delineate the boundaries of objects receiving visual attention, effectively translating human gaze behavior into structured object-level representations without requiring task-specific training or fine-tuning.

0.3.2 Planned Practical Steps

The planned next steps can be divided into two main parts. The first part focuses on the optimization of the saliency object detection process, while the second part focuses on the extraction of insights from the segmented objects, based on an exploratory data analysis (Tukey, 1977).

As discussed in the previous section, the current approach offers several options for improvement. These include image preprocessing, the adjustment of threshold values, the use of box prompts instead of point prompts, and the exploration of additional clustering methods such as k means. Moreover, it is possible to add further steps between the main stages of the workflow in order to create more stable and consistent results. As a last possibility, the model can be fine-tuned, using existing scientific datasets such as WXSOD or PASCAL-S (CCVL, 2018; Quan et al., 2025), which already include saliency masks. The overall goal of this first step is to produce the best possible saliency masks for social media images. Better masks allow for a more reliable extraction of insights in the next step.

After the optimization step, the quality of the segmented masks must be evaluated. This evaluation includes three main questions. First, it must be examined if the masks truly represent the salient parts of the image. Second, the mask quality must be assessed by measuring how well the masks fit the expected important regions. Third, it must be analyzed whether certain types of images work better or worse with saliency based segmentation. This helps identify strengths and limitations of the approach for different kinds of social media content.

Furthermore, the generated masks allow for additional exploratory fields of analysis that can be grouped into three areas: user insights, content insights, and accessibility support. The user related area includes predictive user profiling, where salient regions help identify which visual elements attract individual users. The content related area includes a deeper understanding of social media images, the detection of clickbait content, and guidance for creators who work with under optimized images. The accessibility related area focuses on focus aware alternative text generation, where the masks help identify the most important visual elements for users with visual impairments. Together, these groups show the wider potential of the approach beyond the core segmentation step.

0.4 Results

0.4.1 Current Results

Regarding the first iteration of our Saliency Object Detection Pipeline, we have successfully segmented some types of social media images. Figure TODO shows an example of a social media image, along with its generated saliency mask. The mask highlights the teacher, the computer screen and the specific area on the sceen, which does represent the salient objects in this image. Also other images, showing small groups of people or single persons have been segmented quite well so far.

However, there are also several limitations, which have been observed in the current results. First, images with very complex scenes or too many objects tend to produce less accurate masks (see Figure TODO). Second, images with text overlays led to only some letters being grouped into the salient region, instead of the full text block (see Figure TODO). Third, images with landscapes or generally without clear focal points were not segmented effectively (see Figure TODO). These limitations indicate that while the current pipeline shows promise, there is still room for improvement in handling a wider variety of social media images.

0.4.2 Expected Results for the Planned Steps

Regarding the planned optimization steps, we expect to see significant improvements in the quality of the saliency masks. By implementing image preprocessing techniques, we anticipate that noise and irrelevant details in the images will be reduced, leading to clearer segmentation results. The other discussed optimization techniques aim to further refine the segmentation process, making it more robust across different types of images. Overall, we strive to achieve more consistently accurate saliency masks, which will enhance the reliability of subsequent analyses.

Further analyses based on the optimized masks are expected to yield valuable insights into user behavior and content characteristics on social media platforms. For instance, by examining which visual elements are most frequently highlighted in the masks, we can infer what types of content are more engaging to users. These insights can inform content creation and moderation strategies. As the second part of our planned work is mostly experimental, pivots and adjustments of the goal and scope might be necessary, which would lead to different expected results.

0.5 Discussion

0.5.1 Limitations

During our research we identified several limitations that shape how the results should be interpreted. These limitations reflect both technical challenges and aspects related to the nature of social media content. First, social media images show a high level of complexity. They include a wide range of content, contexts and formats. This diversity makes it difficult to define what should be considered salient across different situations. It also reduces the generalisability of models that are trained on more uniform data sources.

Second, we encountered technical constraints. Modern transformer based models that support tasks such as image captioning are often very large and require considerable computational resources. In many practical settings these models cannot be used directly or must be simplified, which can reduce performance. Third, the ground truth data available in existing datasets reflects subjective human judgement. What is perceived as salient can differ between individuals, which introduces uncertainty into training and evaluation. Finally, there are currently no datasets designed specifically for salient object detection in the context of social media. Most available datasets are collected in more controlled environments and do not capture the characteristics of social media content. This limits the ability to develop and evaluate models that address this specific setting.

0.5.2 Future Research

Future research can build on the findings of this seminar and explore areas that lie beyond its scope. One important direction is the development of datasets that focus specifically on social media content. Such datasets would give models the opportunity to learn from examples that reflect the diversity, style and context that are characteristic of images shared online. Another promising direction is the investigation of lightweight models for social media image analysis. Since many existing approaches rely on large and resource intensive architectures, identifying smaller and more efficient models could improve accessibility and practical use.

Further work may also examine how multimodal data can support salient object detection. Textual elements such as image captions can provide additional context and may enhance model performance when integrated with visual information. Moreover, researchers could explore new applications of salient object detection within social media analysis. This may include areas such as content understanding, user behaviour studies and automated moderation, where identifying salient elements may enable deeper insights and more effective tools.

0.6 Conclusion

- We explored the topic of Salient Object Detection, specifically in the context of Social Media Images.
- We reviewed existing methods and models for Salient Object Detection.
- We identified the unique challenges posed by Social Media Images, such as diverse content and formats.
- We implemented a first prototype to segment salient objects in social media images using a zero-shot approach.
- We discussed the limitations of our approach and proposed next steps for our research.

A Appendix

TODO: Add result pictures and/or our code here

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