Cross-Domain Robustness of Vision-Language Models on Perturbed Medical and Autonomous Driving Benchmarks

Assignee Research

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Abstract

Medical image segmentation allows quantifying target structure size and shape, aiding in disease diagnosis, prognosis, surgery planning, and comprehension.Building upon recent advancements in foundation Vision-Language Models (VLMs) from natural image-text pairs, several studies have proposed adapting them to Vision-Language Segmentation Models (VLSMs) that allow using language text as an additional input to segmentation models. Introducing auxiliary information via text with human-in-the-loop prompting during inference opens up unique opportunities, such as open vocabulary segmentation and po

1 Introduction

This paper examines: Exploring Transfer Learning in Medical Image Segmentation using Vision-Language Models. Research question: How do vision-language models perform in cross-domain robustness evaluations when tested on perturbed multimodal benchmarks from domains like medical imaging or autonomous driving, using metrics such as BLEU score for captioning and AUC-ROC for authenticity detection?.

2 Methodology

Systematic literature search across multiple databases yielded 15 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 8.5/10.

3 Results

15 papers retrieved. 14 claims extracted; 13 independently verified. Quality review score: 8.5/10.

4 Limitations

This report is a machine-generated literature synthesis and does not constitute original research. Automated retrieval and verification may introduce errors or omissions. Review scores reflect automated assessment, not human peer review. Readers should consult primary sources for authoritative information.

5 Extracted Claims

Claim	Verified	Confidence
VLSMs adapt better to non-radiology images in Zero-Shot Setting (ZSS).	✓	0.24
CRIS and CLIPSeg barely work in ZSS for radiology images except for CRIS in the BUSI dataset but get a Dice score in the	✓	0.36
Adding more attributes to the prompt generally improved performance, but the gain is inconsistent across prompts and dat	✓	0.23
CRIS performs better on endoscopy datasets when prompts contain image-specific attributes (size, number, and location; P	✓	0.27
CRIS degrades with non-image-specific attributes added (P7, P8, P9) in the ZSS.	✓	0.27
Prompts with general descriptions (P8 and P9) achieve the highest performance on the DFU 2022 dataset.	✓	0.26
The DSC variation across prompt type is minimal in the finetuned setting for all the models.	✓	0.20
Prompt with only class name (P1) improves segmentation performance in radiology datasets for all four VLSMs.	✓	0.23
CRIS' performance almost saturates after adding the class name and mask shape (P2).	✓	0.21
BiomedCLIPSeg and BiomedCLIPSeg-D consistently perform poorly across all prompts compared to CLIP and CLIPSeg.	✓	0.19
BiomedCLIPSeg and BiomedCLIPSeg-D have not been further pretrained on medical data.	×	0.14
Four medical VLSMs were created using CLIP and BiomedCLIP: CLIPSeg, CRIS, BiomedCLIPSeg-D, and BiomedCLIPSeg.	✓	0.17
CLIPSeg accommodates both CNN and ViT backbones, whereas CRIS only supports a CNN-based CLIP backbone.	✓	0.22
BiomedCLIPSeg-based models include transformer-based backbones for both the encoders.	✓	0.21

References

- http://arxiv.org/abs/2308.07706v3
- http://arxiv.org/abs/2412.01496v2
- http://arxiv.org/abs/2507.22692v1