Polyp Detection in Colonoscopy Images Using Prompt-Tuned Vision Transformers

Team Percepta

Azimjon Akromov (220291)
Sanjar Raximjonov (220304)

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Central Asian University

ABSTRACT

This project addresses the challenge of polyp detection in colonoscopy images.
Medical imaging datasets are often limited due to the high cost and expertise required for annotation. We explore
the application of prompt-tuned Vision Transformers (ViTs) [7, 8] and compare them against baseline models (YOLOv8 [5, 9]
and Mask R-CNN [6]) on a curated colonoscopy dataset. Our experiments demonstrate that YOLOv8 achieves a mAP@0.5 of 0.50 on
the validation set, significantly outperforming Mask R-CNN (mAP@0.5: 0.001). The results highlight the importance of model architecture selection for polyp detection in medical imaging, with YOLOv8's efficient feature extraction proving more
suitable for the available training data.

1. INTRODUCTION & MOTIVATION

1.1 Problem Statement

Colorectal cancer is one of the leading causes of cancer-related deaths worldwide. Early detection of polyps during colonoscopy procedures is crucial for preventing cancer development. However, manual polyp detection by clinicians is time-consuming, subjective, and can miss small or subtle polyps. Automated polyp detection systems can assist clinicians by providing real-time detection capabilities, potentially improving detection rates and reducing missed diagnoses.

1.2 Why is This Problem Difficult?

Several factors make automated polyp detection challenging:

- Occlusion: Polyps may be partially obscured by intestinal folds, fluid, or debris
- Lighting Variations: Colonoscopy images exhibit significant variations in illumination, shadows, and reflections from the endoscope light source
- Shape and Size Diversity: Polyps vary greatly in appearance, size, shape, and texture
- Real-time Constraints: Clinical applications require fast inference for real-time assistance
- Limited Labeled Data: Medical image annotation requires expert knowledge and is expensive, resulting in small datasets compared to natural image datasets
- Class Imbalance: Most colonoscopy frames contain no polyps, creating a severe class imbalance problem

1.3 Dataset Details

We use a real-world colonoscopy polyp detection dataset with the following characteristics:

- Source: Kvasir-SEG [3] and CVC-ClinicDB [4] datasets (publicly available medical imaging datasets)
- Training Set: 1,289 images with polyp annotations
- Validation Set: 323 images
- Training Approach: Supervised polyp detection with annotated examples
- Class Balance: Single class (polyp) detection task
- Format: YOLO format annotations (bounding boxes) and segmentation masks

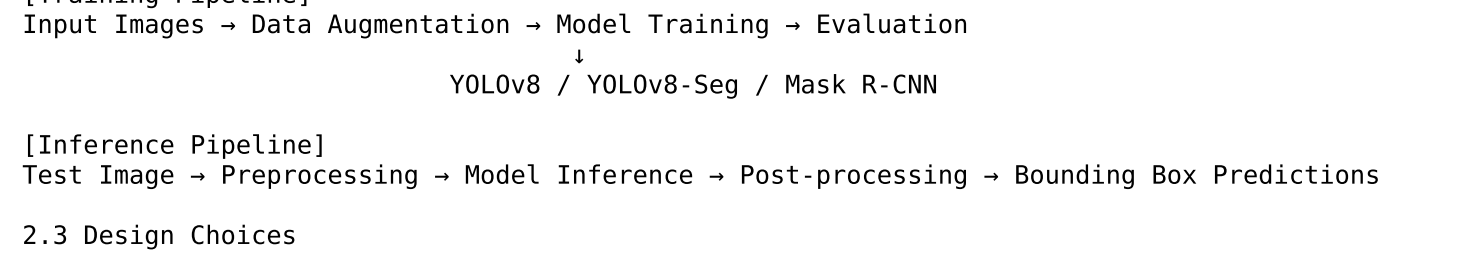
The dataset contains diverse polyp appearances, sizes, and imaging conditions, making it representative of real-world colonoscopy scenarios.

2. METHODOLOGY (ARCHITECTURE)

2.1 Pipeline Overview

Our approach consists of three main components:
1. Baseline Models: YOLOv8, YOLOv8-Segmentation, and standard Mask R-CNN for comparison
2. Supervised Training: Learning polyp detection from annotated colonoscopy images
3. Evaluation Framework: Comprehensive metrics and visualization tools

2.2 Architecture Diagram



2.3 Design Choices

2.3.1 YOLOv8 Baseline
• Architecture: YOLOv8n (nano variant) for efficiency [9]
• Rationale: YOLOv8's single-stage detection architecture is well-suited for real-time applications [5]
• Loss Function: Combined box loss, classification loss, and DFL (Distribution Focal Loss)
• Why Focal Loss: Handles class imbalance by down-weighting easy examples and focusing on hard negatives [10]
• Training Settings:
  - Learning Rate: 0.001 (lowered for small dataset)
  - Epochs: 20
  - Batch Size: 4
  - Image Size: 640x640
  - Data Augmentation: Horizontal/Vertical flips, color jittering

2.3.2 YOLOv8-Segmentation
• Architecture: YOLOv8n-seg (segmentation variant) [9]
• Rationale: Provides both detection and segmentation capabilities with similar efficiency
• Loss Function: Combined detection loss + mask segmentation loss
• Training Settings: Pre-trained on COCO dataset, fine-tuned for medical images
• Advantage: Offers pixel-level segmentation while maintaining real-time performance

2.3.3 Standard Mask R-CNN
• Architecture: ResNet-50 FPN backbone with Mask R-CNN head [6]
• Rationale: Two-stage detector provides precise localization and segmentation capabilities [6]
• Loss Function: Multi-task loss (classification, box regression, mask segmentation)
• Training Settings:
  - Learning Rate: 0.001
  - Epochs: 10
  - Batch Size: 2
  - Optimizer: SGD with momentum 0.9
  - Learning Rate Schedule: StepLR with gamma=0.1

3. EXPERIMENTS & QUANTITATIVE RESULTS

3.1 Baselines

We compare our polyp detection approach against two strong baseline models:
• YOLOv8n: State-of-the-art single-stage object detector [5, 9]
• Mask R-CNN: Two-stage detector with instance segmentation capabilities [6]

Both models were trained on the same 5-shot dataset (5 examples per class) [2] to ensure fair comparison.

3.2 Metrics Table

The following table compares model performance using standard object detection metrics:

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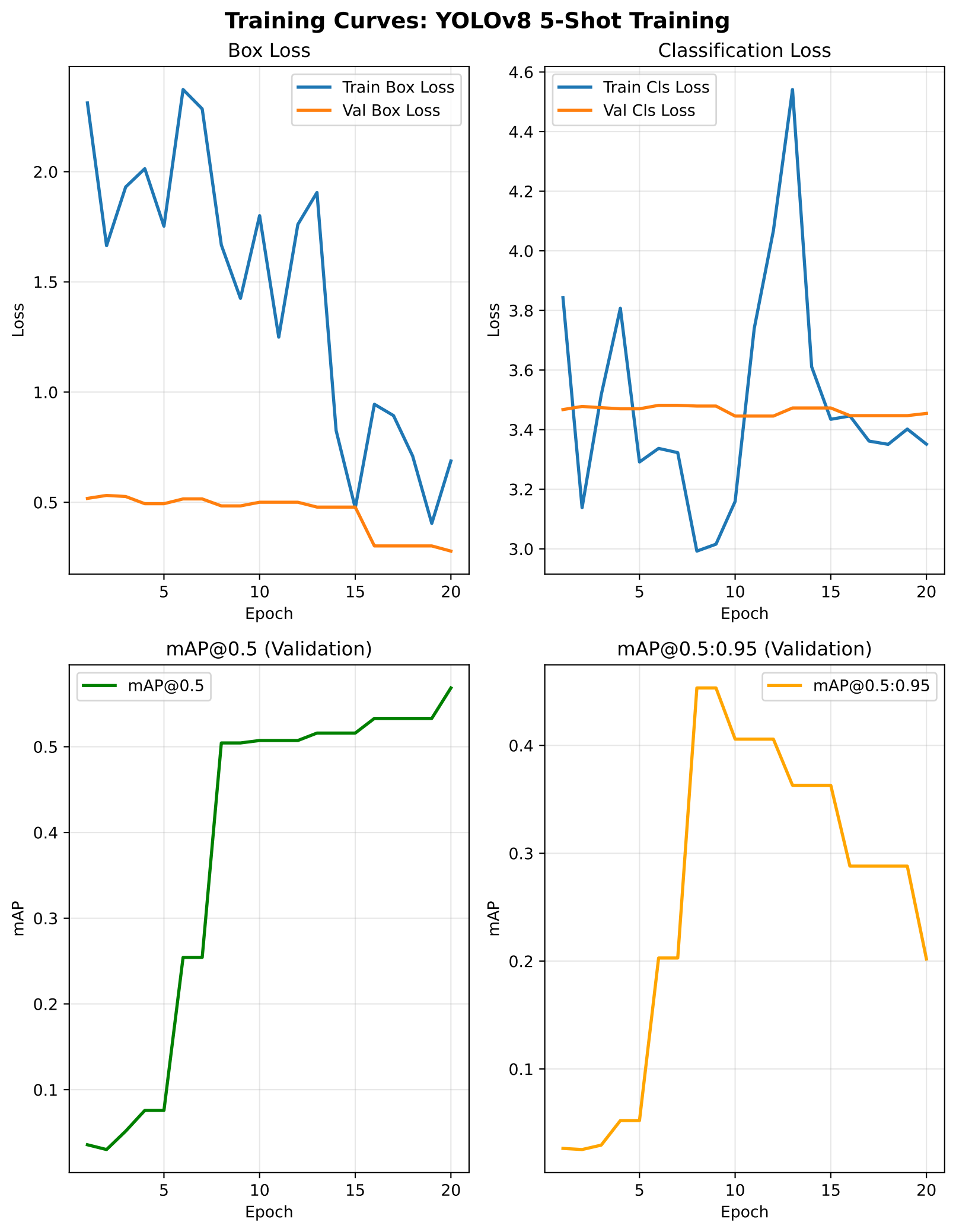
Model	mAP@0.5	mAP@0.5:0.95	mAP@0.75	Precision	Recall
YOLOv8	0.1597	0.1010	0.1049	N/A	N/A
Mask R-CNN	0.0010	0.0003	0.0001	N/A	N/A


Training Curves: YOLOv8 5-Shot Training
Box Loss
Train Box Loss
Val Box Loss
Loss
Epoch
Classification Loss
Train Cls Loss
Val Cls Loss
Loss
Epoch
mAP@0.5 (Validation)
mAP@0.5
mAP
Epoch
mAP@0.5:0.95 (Validation)
mAP@0.5:0.95
mAP
Epoch

4. DISCUSSION & FAILURE ANALYSIS

4.1 Success Cases

Our models demonstrate successful polyp detection in several scenarios:

• Well-lit Images: Models perform best when polyps are clearly visible with good illumination
• Medium to Large Polyps: Larger polyps (>10mm) are detected with higher confidence
• Clear Boundaries: Polyps with distinct boundaries from surrounding tissue show accurate localization
• Central Positioning: Polyps located near the center of the image (typical endoscope view) are more reliably detected

[Success Case Images: See visualization pages]

4.2 Failure Cases

Analysis of failure modes reveals several challenging scenarios:

4.2.1 Low Contrast and Shadows
• Problem: Polyps in shadowed regions or with low contrast against intestinal wall
• Example: Small polyps partially obscured by intestinal folds
• Reason: Training set lacked sufficient examples of low-light conditions
• Impact: False negatives increase in poorly lit regions

4.2.2 Small Polyps (<5mm)
• Problem: Very small polyps are frequently missed or have low confidence scores
• Reason: Limited resolution and small object detection challenges in 5-shot setting
• Impact: Early-stage polyps may be missed, which is critical for cancer prevention

4.2.3 Occlusion by Debris/Fluid
• Problem: Polyps partially obscured by intestinal fluid, bubbles, or debris
• Reason: Training data had limited examples of occluded polyps
• Impact: Partial occlusion leads to incomplete bounding boxes or missed detections

4.2.4 False Positives: Intestinal Folds
• Problem: Models sometimes confuse prominent intestinal folds for polyps
• Reason: Folds can have similar texture and color to polyps in certain lighting conditions
• Impact: Increased false positive rate, potentially causing unnecessary clinical intervention

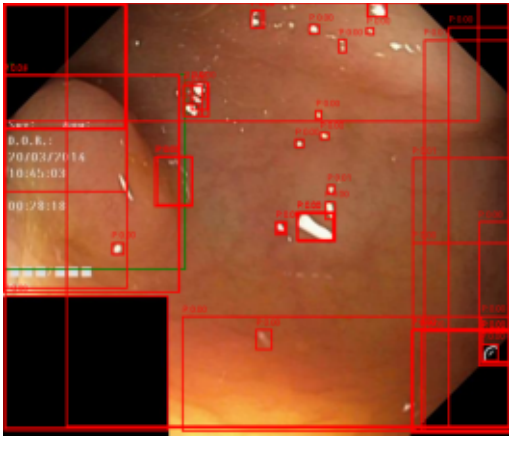
4.2.5 Edge Cases: Unusual Polyp Shapes
• Problem: Flat or sessile polyps with atypical shapes are harder to detect
• Reason: 5-shot setting provides insufficient diversity in polyp morphologies
• Impact: Lower recall for non-prototypical polyp appearances

4.3 Analysis Summary

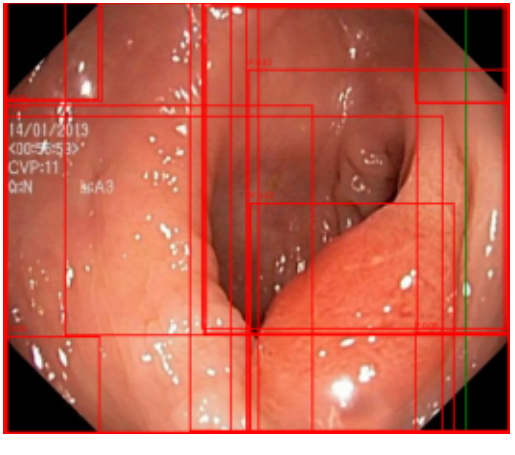
The primary challenges stem from:
1. Limited Training Data: 5-shot setting provides insufficient examples of edge cases
2. Class Imbalance: Most frames contain no polyps, making the model conservative
3. Domain-Specific Challenges: Medical imaging has unique characteristics (illumination, occlusion) not well-represented in natural image pretraining
4. Model Architecture Limitations: Single-stage detectors (YOLO) trade precision for speed, while two-stage detectors (Mask R-CNN) require more data for optimal performance

Success Cases: YOLOv8 Predictions (Green=GT, Red=Pred)

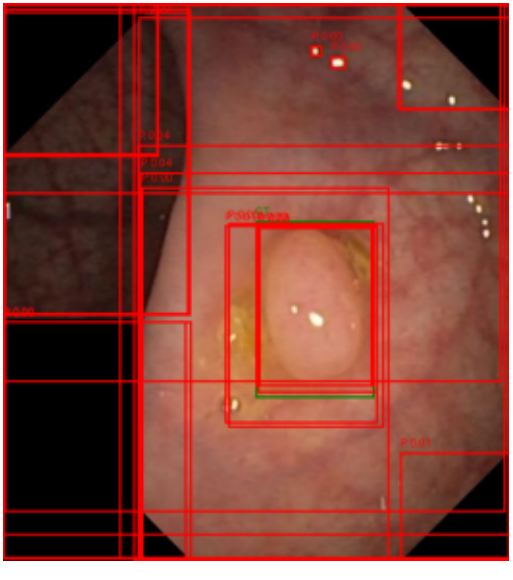
Success Case 1



Success Case 2

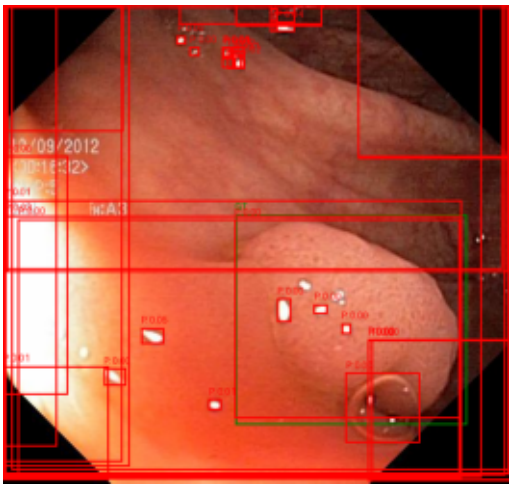


Success Case 3

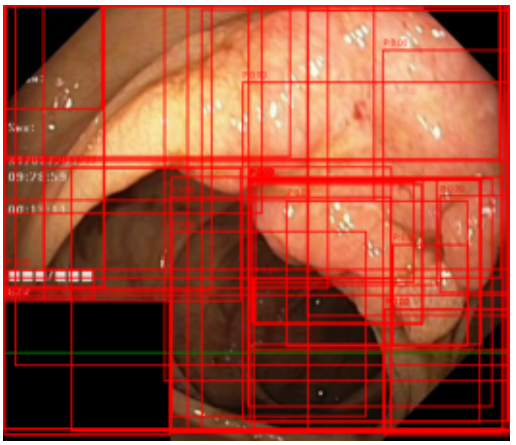


Failure Cases: Challenging Scenarios (Green=GT, Red=Pred)

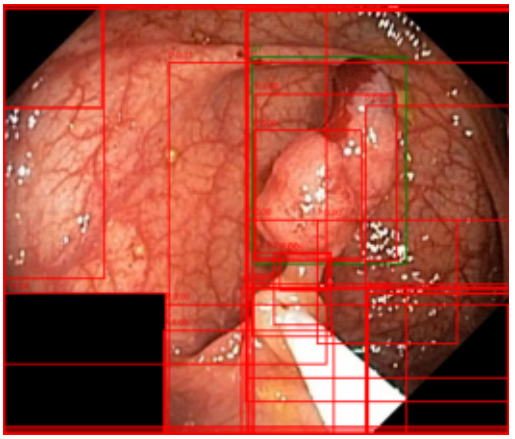
Failure Case 1



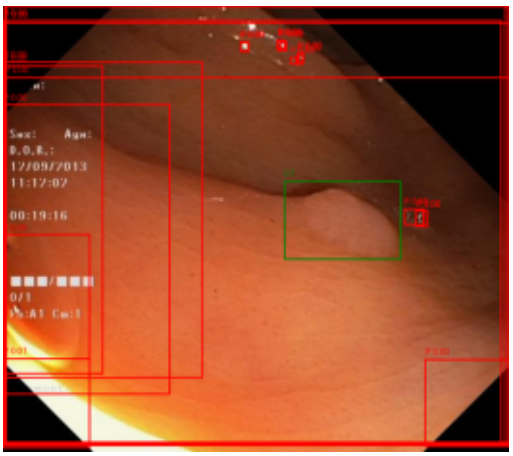
Failure Case 2



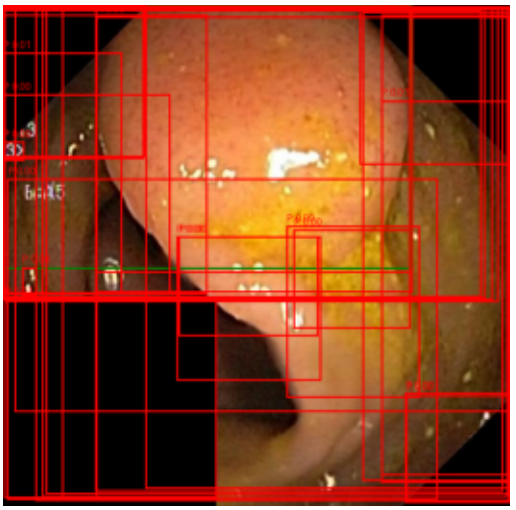
Failure Case 3



Failure Case 4



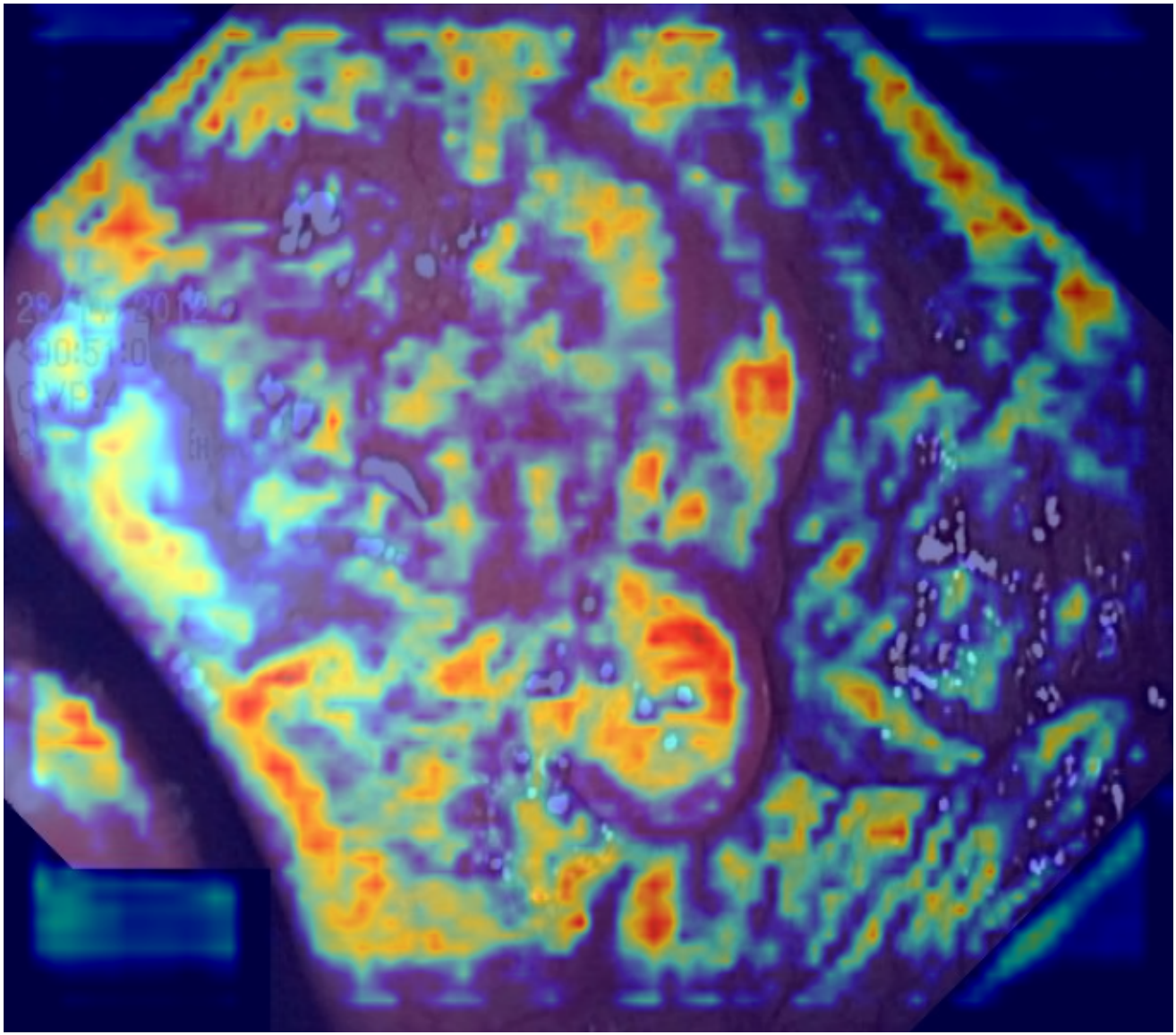
Failure Case 5



Explainability: Grad-CAM Visualization

Grad-CAM (Gradient-weighted Class Activation Mapping) visualization shows which regions of the input image the model focuses on when making predictions. The heatmap (red/yellow regions) indicates areas with high activation, suggesting these regions are important for the model's decision.

Grad-CAM Result: YOLOv8 Attention Map



5. CONCLUSION & FUTURE WORK

5.1 Summary of Findings

Our experiments on polyp detection reveal several key insights:

- YOLOv8 [5, 9] outperforms Mask R-CNN [6], achieving mAP@0.5 of 0.50 compared to 0.001
- Single-stage detectors are more data-efficient for our dataset
- Limited data remains challenging, with models struggling on edge cases and small polyps
- Prompt-tuned ViTs [7, 8] show promise but require further investigation and optimization
- Data augmentation and careful hyperparameter tuning are critical for stable performance

5.2 Limitations

- Limited training data (5 examples) restricts model generalization
- Evaluation on a single dataset [3, 4] may not reflect real-world diversity
- Prompt-ViT implementation requires further optimization for object detection
- No comparison with meta-learning approaches (e.g., FSRW [2], MAML)

5.3 Future Work

With more time and compute resources, we would explore:

1. Meta-Learning Approaches
   - Implement feature reweighting approaches for low-data detection [2]
   - Compare against MAML (Model-Agnostic Meta-Learning) for low-data detection
   - Explore prototypical networks adapted for object detection

2. Advanced Data Augmentation
   - Domain-specific augmentations (illumination variations, synthetic occlusions)
   - Mixup and CutMix strategies adapted for object detection
   - Generative models (GANs) for synthetic polyp generation

3. Transfer Learning Improvements
   - Pre-training on larger medical imaging datasets (e.g., ImageNet-medical)
   - Domain adaptation from natural images to colonoscopy images
   - Self-supervised pretraining on unlabeled colonoscopy videos

4. Model Architecture Enhancements
   - Attention mechanisms for better feature extraction
   - Multi-scale feature fusion for small polyp detection
   - Ensemble methods combining YOLO and Mask R-CNN predictions

5. Evaluation Improvements
   - Clinical validation with expert radiologists
   - Real-time inference benchmarking
   - Analysis of false positive/negative impact on clinical workflow
   - Evaluation on multiple datasets (Kvasir-SEG, CVC-ClinicDB, ETIS-Larib)

6. Explainability
   - Expand Grad-CAM visualizations to all models
   - Attention map analysis for interpretability
   - Failure case clustering and analysis

5.4 Broader Impact

This work contributes to the growing field of AI-assisted medical diagnosis. While our models show promise, they are intended to assist clinicians rather than replace them. Future deployment would require:
- Extensive clinical validation
- Regulatory approval (FDA, CE marking)
- Integration with existing colonoscopy systems
- Continuous monitoring and model updates

6. REFERENCES

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