DLMI - Final Project

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AGENDA

1. Introduction
2. Methodology
3. Experiment and Result
4. Conclusion

Introduction

1. Data Source
2. Dataset and Exploratory Data Analysis

Introduction - Data Source

- All participants are **not allowed to use external medical image datasets** during this challenge. The foundation models in other areas, such as natural images and natural language processing area, are allowed.
- In the setting of our tasks, **the few-shot number is counted by the number of patients rather than the number of images**. All participants can only use corresponding few-shot samples in the training set. **Using the full training set is not allowed**.

Introduction - Dataset

Task 1: Thoracic Disease Screening (ChestDR)

Chest X-ray is a regularly adopted imaging technique for daily clinical routine. Many thoracic diseases are reported, and further examinations are recommended for differential diagnoses. Due to the large amount and fast reporting requirements in certain emergency facilities, a swift screening and reporting of common thoracic diseases could largely improve the efficiency of the clinical process.

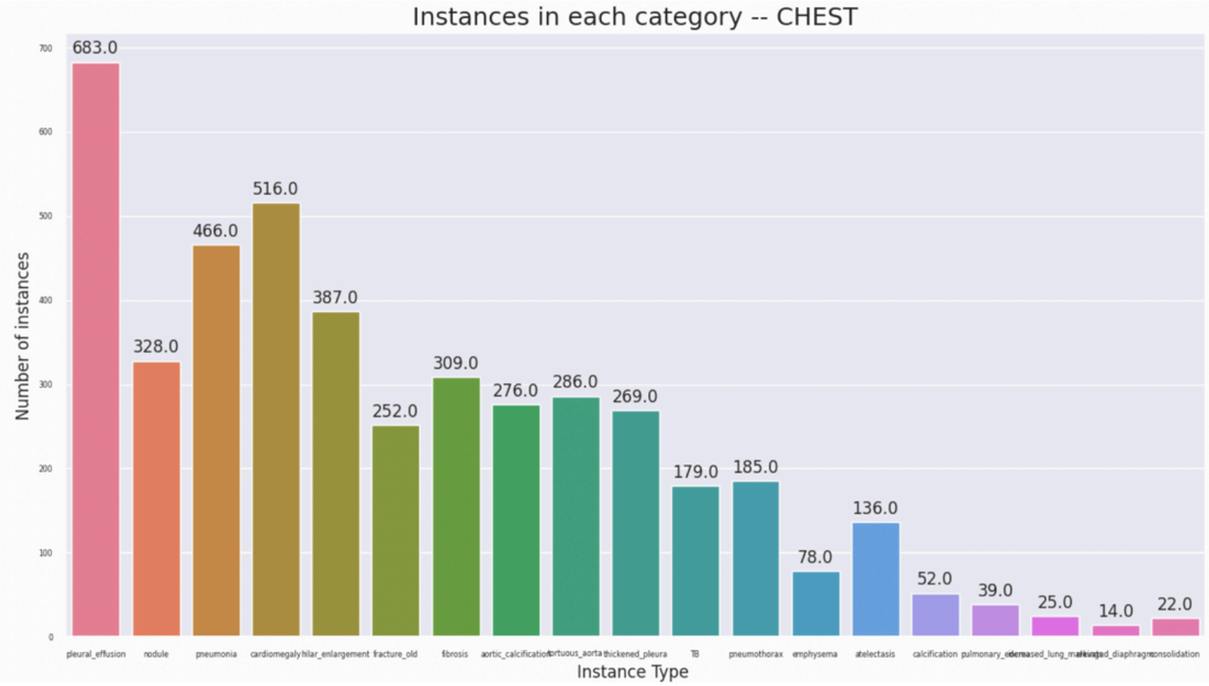
Pleural effusion,
Pneumonia, Atelectasis

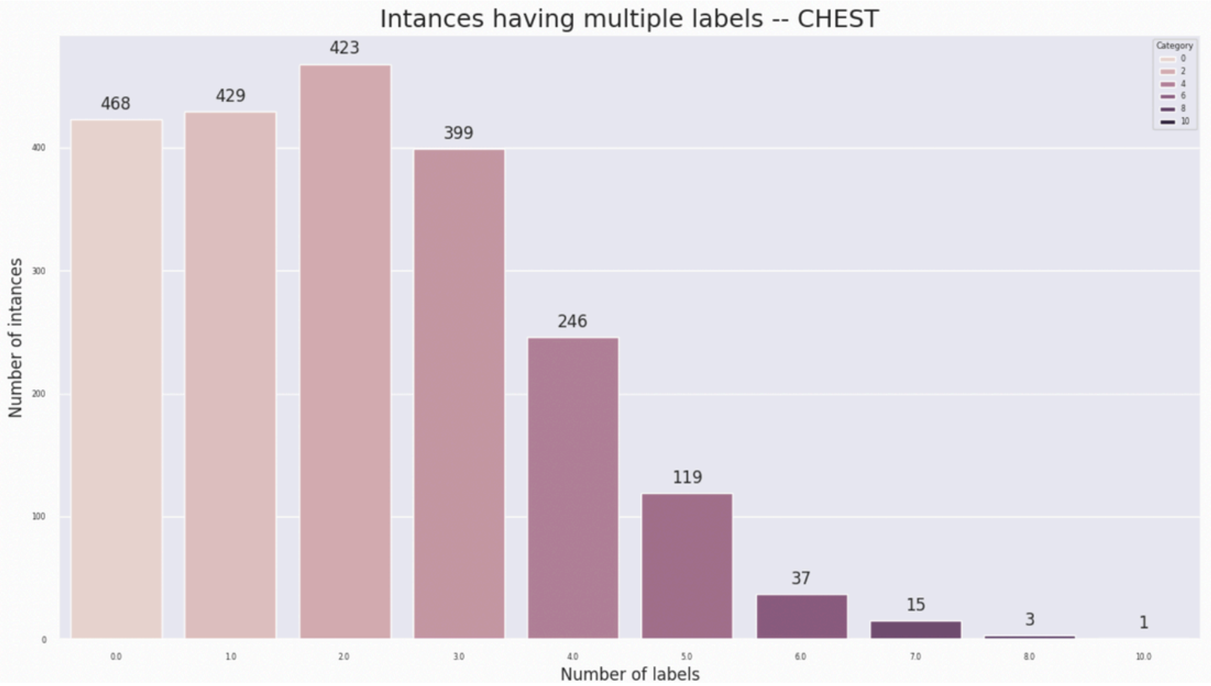
Abnormality	#Sample	Abnormality	#Sample
Cardiomegaly	1300	TB	305
Pleural effusion	1266	Pneumothorax	284
Pneumonia	898	Atelectasis	199
Hilar enlargement	758	Emphysema	159
Nodule	665	Calcification	104
Aortic calcification	645	Pulmonary edema	86
Tortuous aorta	612	Increased lung markings	53
Fibrosis	532	Consolidation	34
Thickened pleura	497	Elevated diaphragm	23
Fracture	429		

Introduction - Dataset

Task 1: Thoracic Disease Screening (ChestDR)

- Among the training dataset, pleural effusion has the highest number of 683 and elevated diaphragm has the lowest number of 14.
- 1 case is labeled with the most 10 tumors detected, and most of the other cases are only labeled with less than 3 tumors.

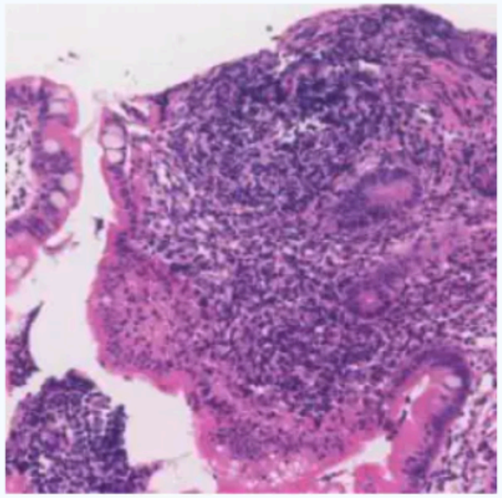




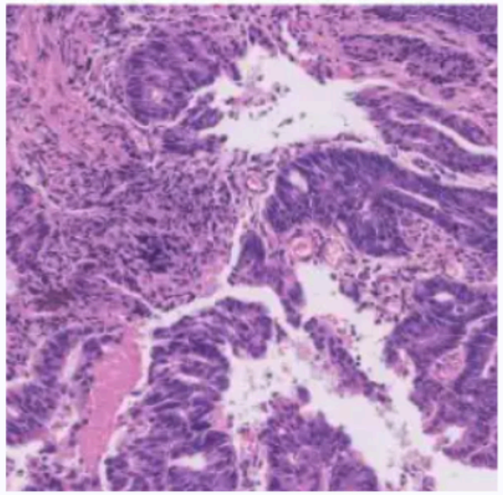
Introduction - Dataset

Task 2: Pathological Tumor Tissue Classification (Colon)

Pathology examination can support detecting early-stage cancer cells in small tissue slices. In the pathologist’ s daily routine, they are required to look over several dozens of tissue slides, a tiresome and tedious job. In clinical diagnosis, quantifying cancer cells and regions is the primary goal for pathologists. The approaches for the classification of pathological tissue patches are desired to ease this process and help screen whether it exists regions of malignant cells in the entire slide in a sliding window manner.



Normal Tissue	
#Sample	6494
#Slide	249

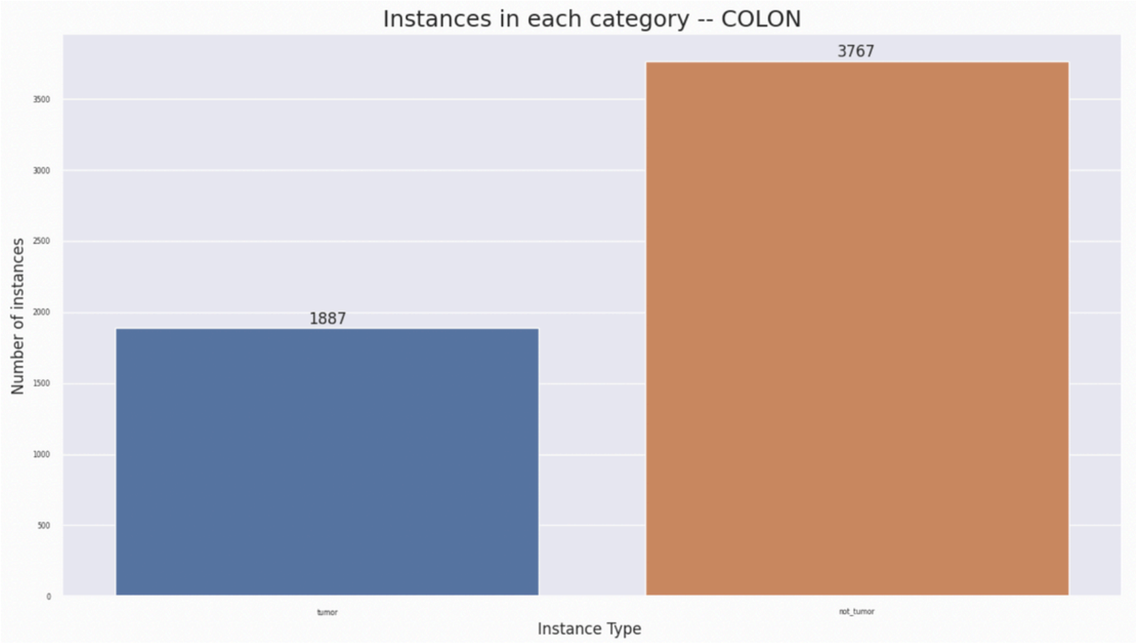


Tumor Tissue	
#Sample	3515
#Slide	147

Introduction - Dataset

Task 2: Pathological Tumor Tissue Classification (Colon)

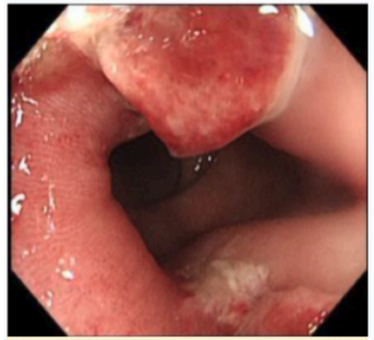
- The number of cases labeled as normal is about twice as many as those labeled as tumors.
- This task can be recognized as a binary classification.



Introduction - Dataset

Task3: Lesion Detection in Colonoscopy Images (Endo)

Colorectal cancer is one of the most common and fatal cancers among men and women around the world. Abnormalities like polyps and ulcers are precursors to colorectal cancer and are often found in colonoscopy screening of people aged above 50. The risks largely increase along with aging. Colonoscopy is the gold standard for the detection and early diagnosis of such abnormalities with necessary biopsy on site, which could significantly affect the survival rate from colorectal cancer. Automatic detection of such lesions during the colonoscopy procedure could prevent missing lesions and reduce the workload of gastroenterologists in colonoscopy.



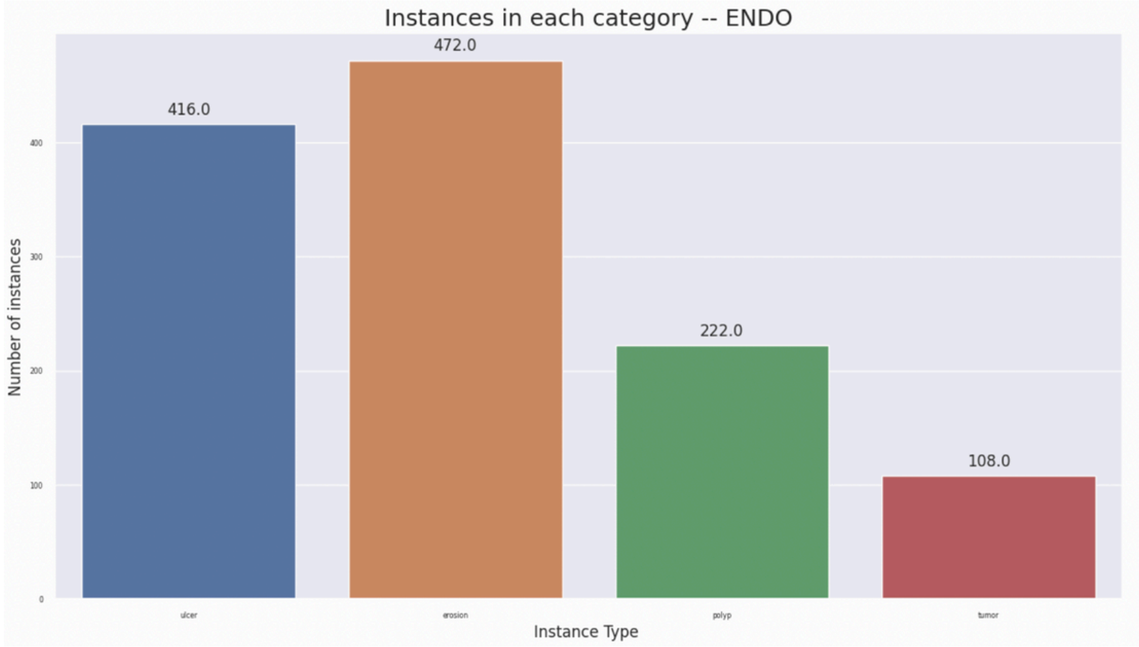
Ulcer, Tumor

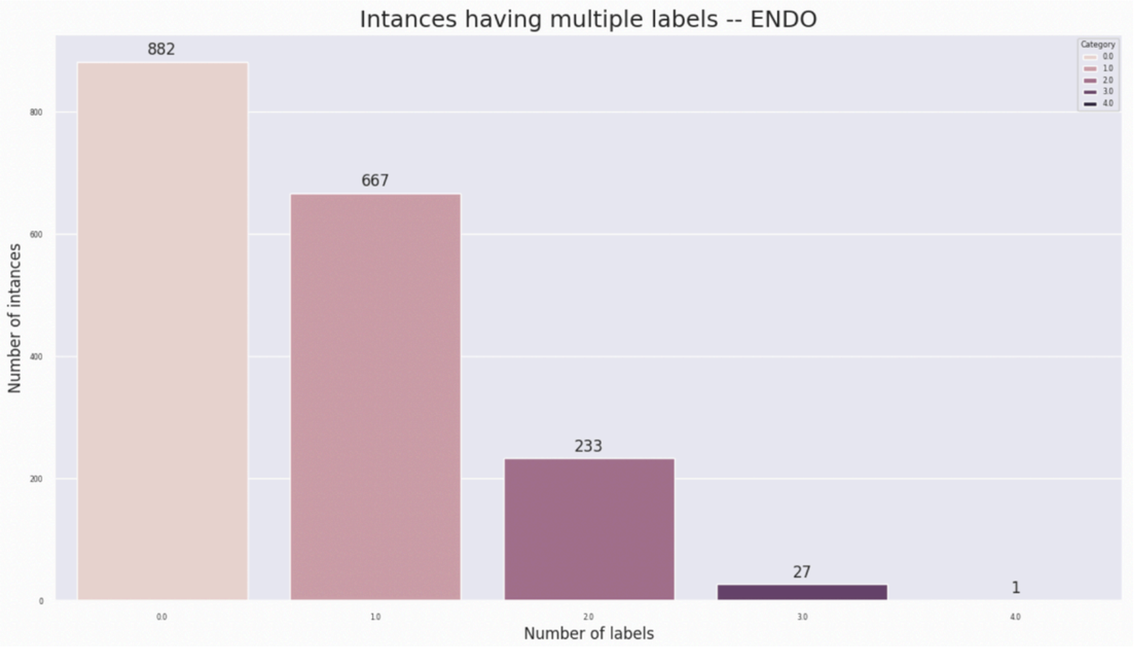
Leison	#Sample	#Study
Ulcer	790	69
Erosion	951	70
Polyp	390	62
Tumor	136	11

Introduction - Dataset

Task3: Lesion Detection in Colonoscopy Images (Endo)

- Erosion has the highest proportion with 472 cases, while tumor has the lowest proportion. However, the overall distribution is not too skewed.
- There is 1 case that is labeled with all four types of lesions, and 882 cases are labeled as having none of these lesions.



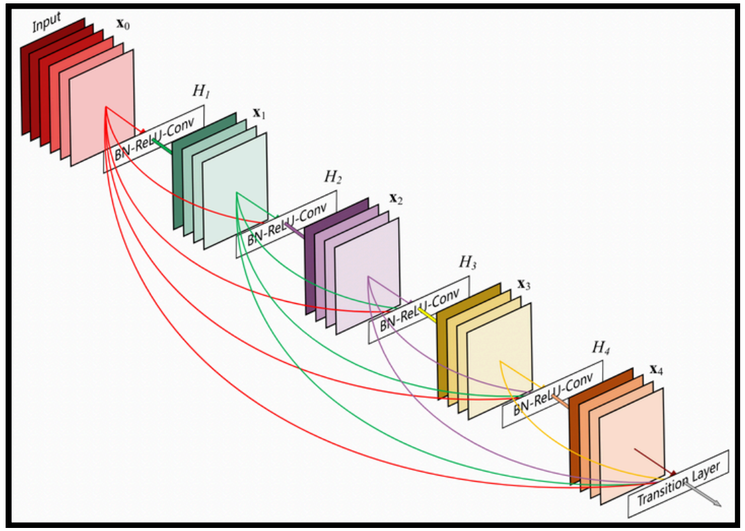


Methodology

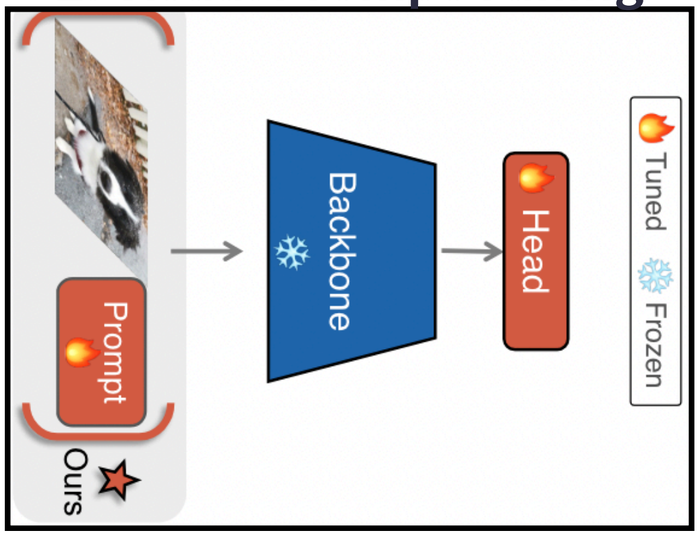
1. Model

Methodology - Model

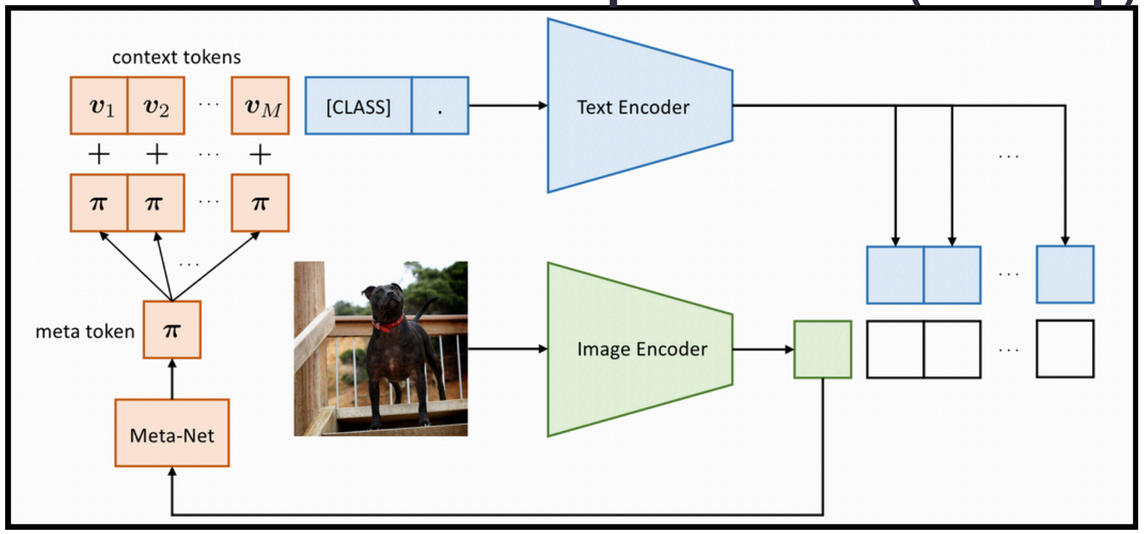
1. Densenet



2. Visual Prompt Tuning

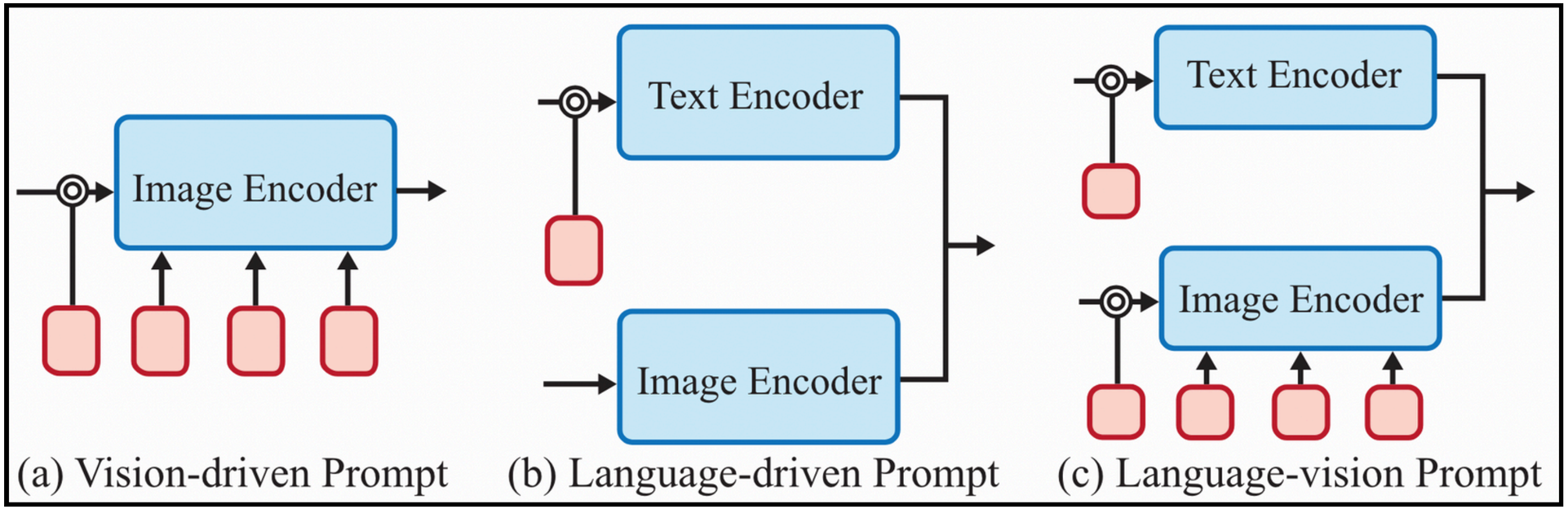


3. Conditional Context Optimization (CoCoOp)



Methodology - Model

- Yu et al. classify **VPT** as a vision-driven prompt method, while **CoCoOp** is classified as a language-driven prompt method.

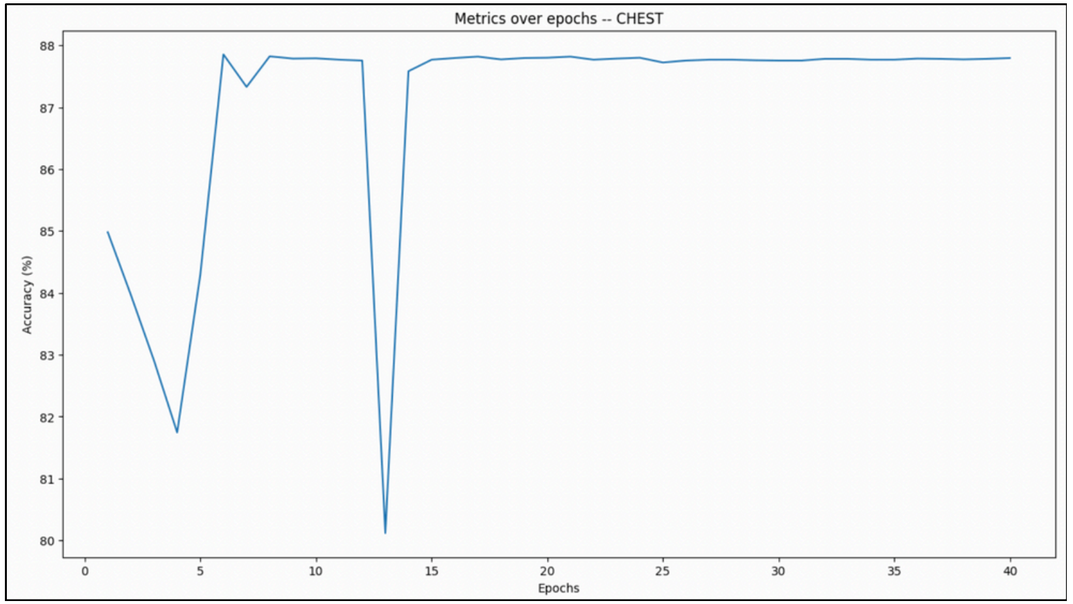


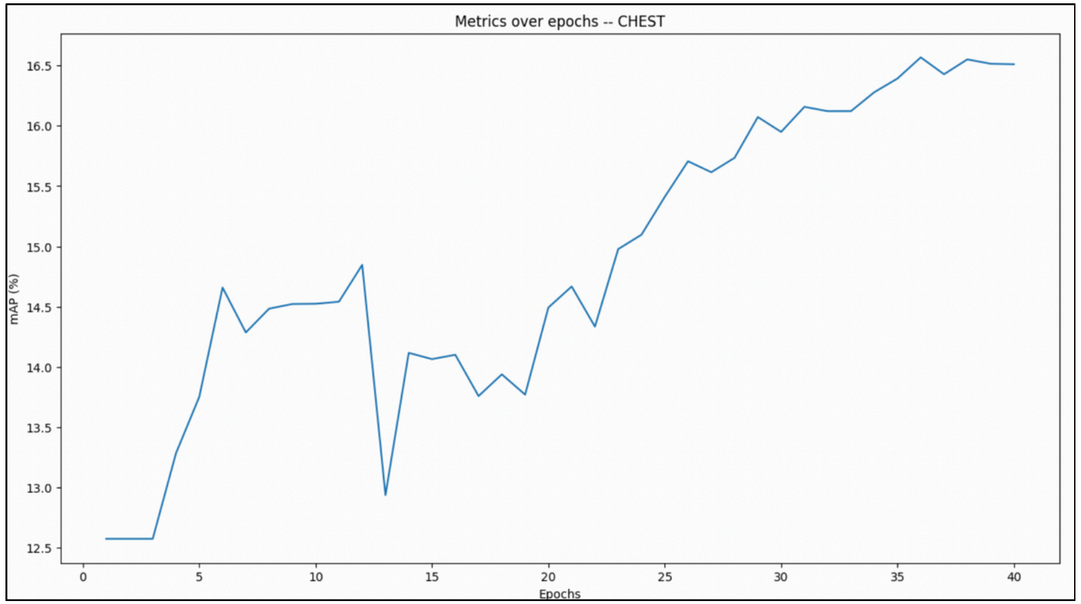
(a) Vision-driven Prompt (b) Language-driven Prompt (c) Language-vision Prompt

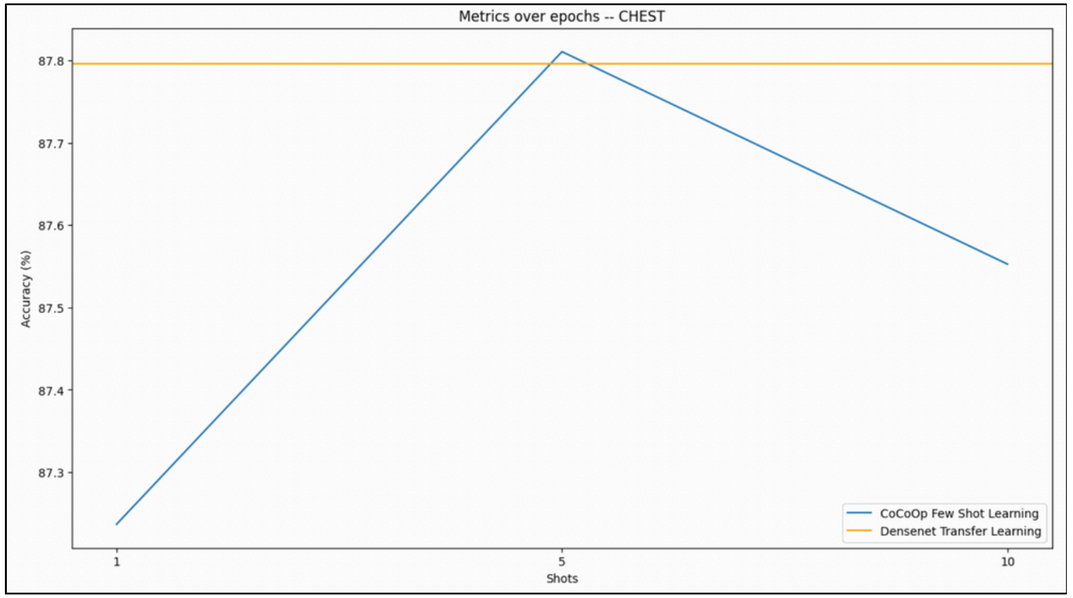
Experiment and Result

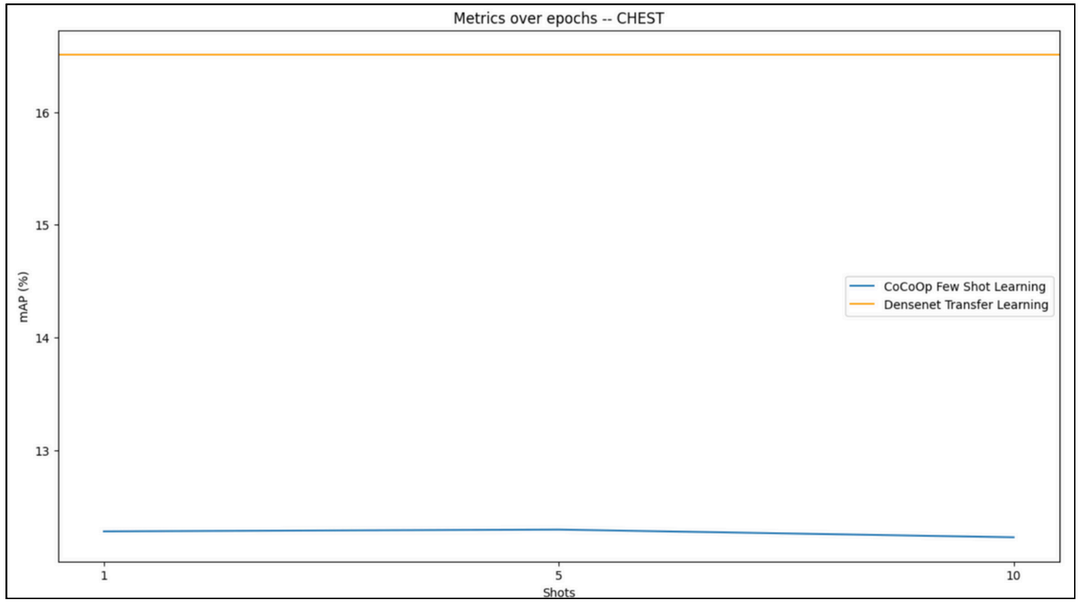
1. ChestDR
2. Colon
3. Endo

Experiment and Result - ChestDR

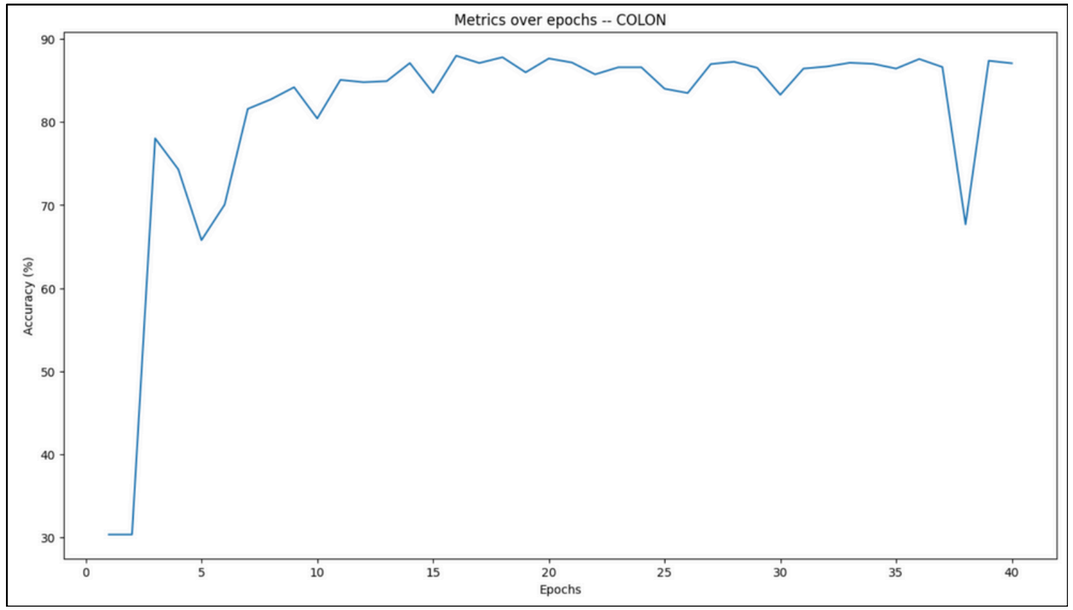


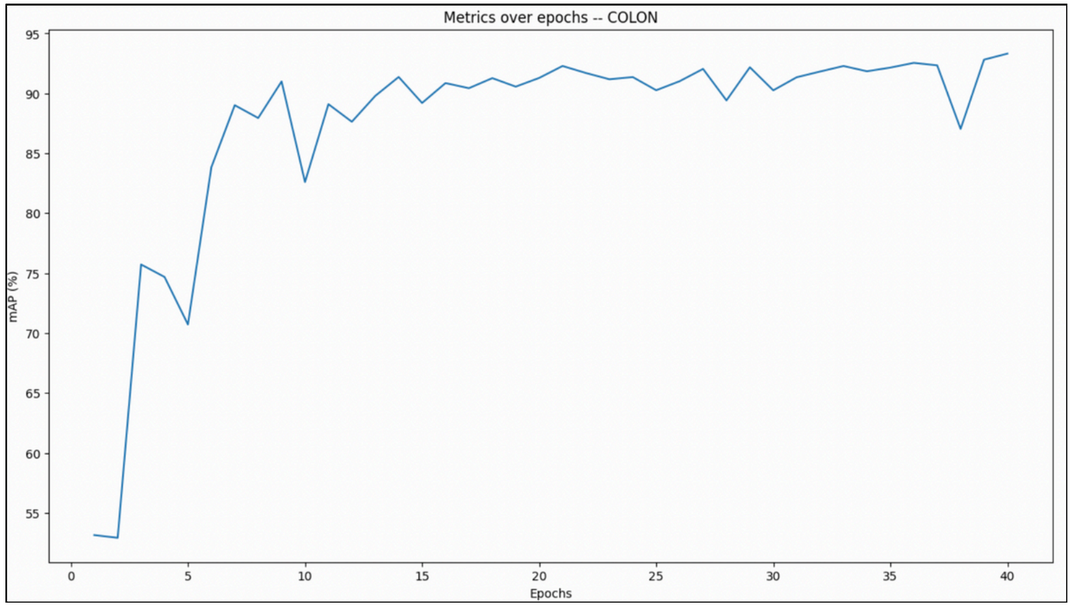


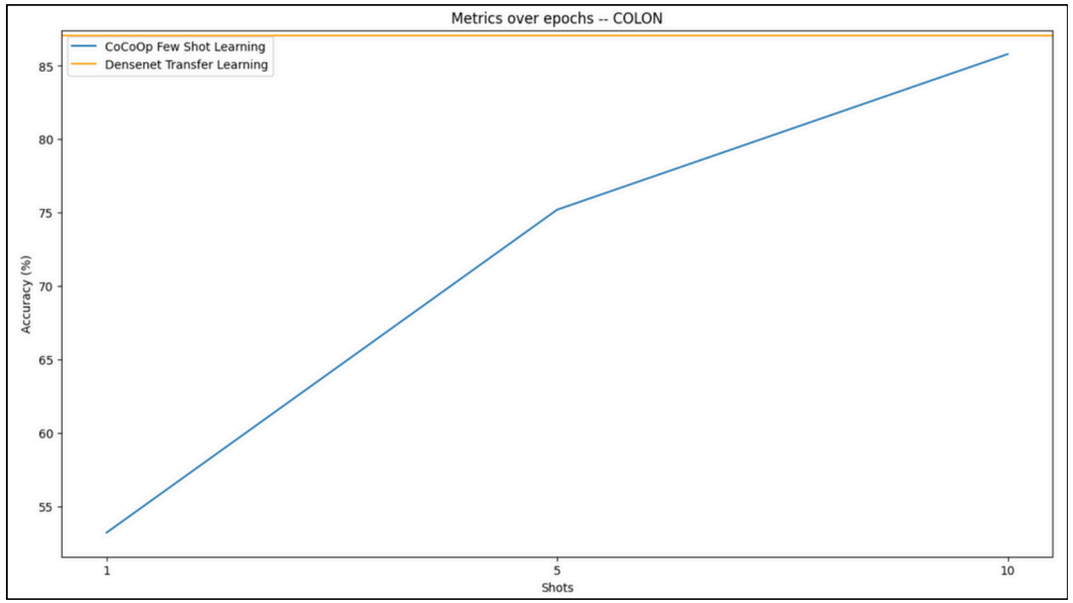


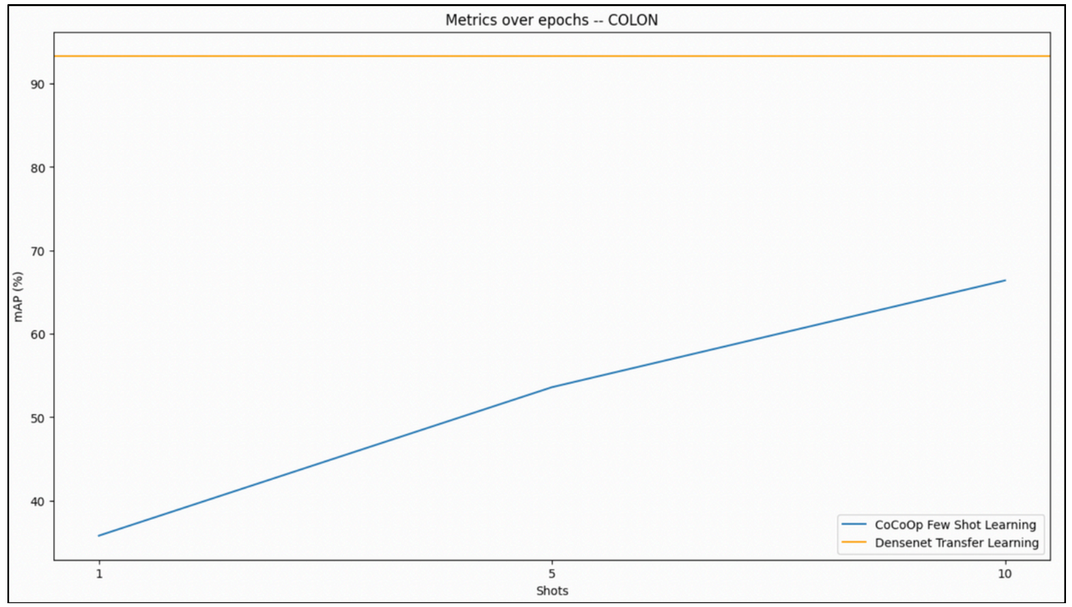


Experiment and Result - Colon

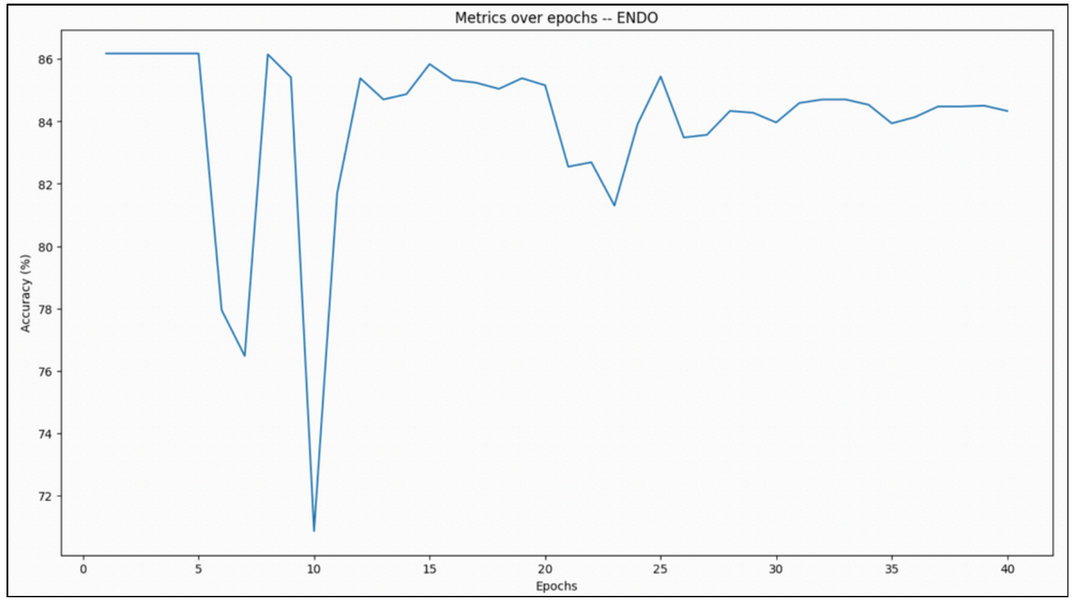


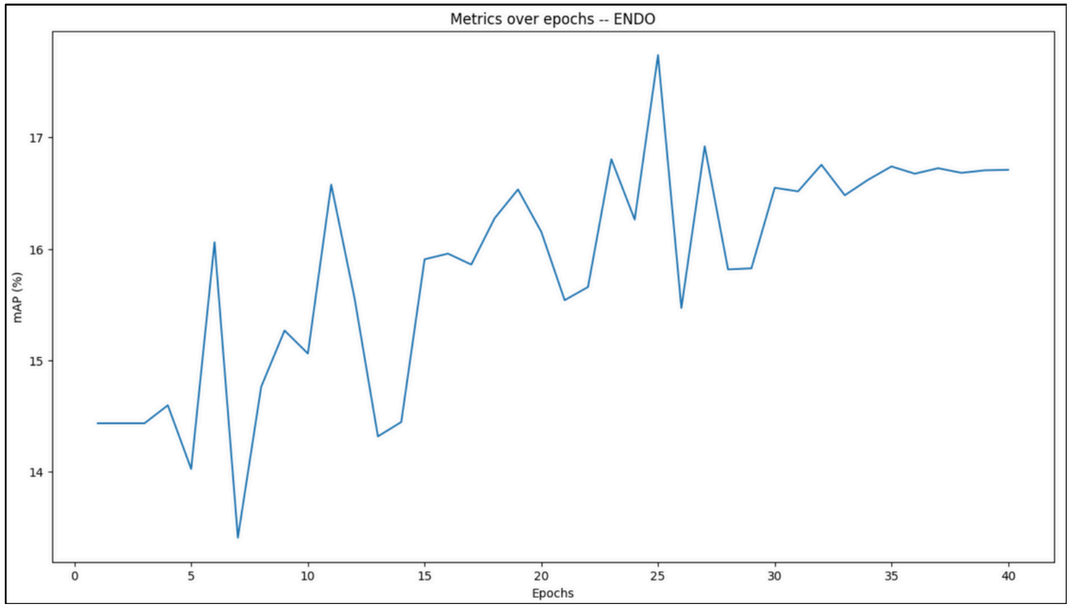


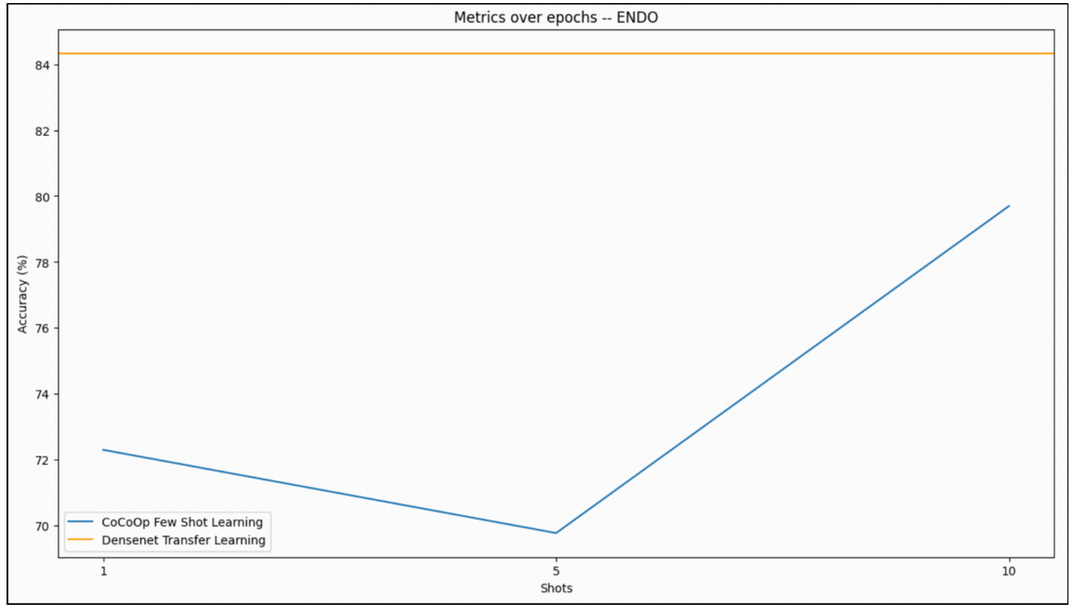


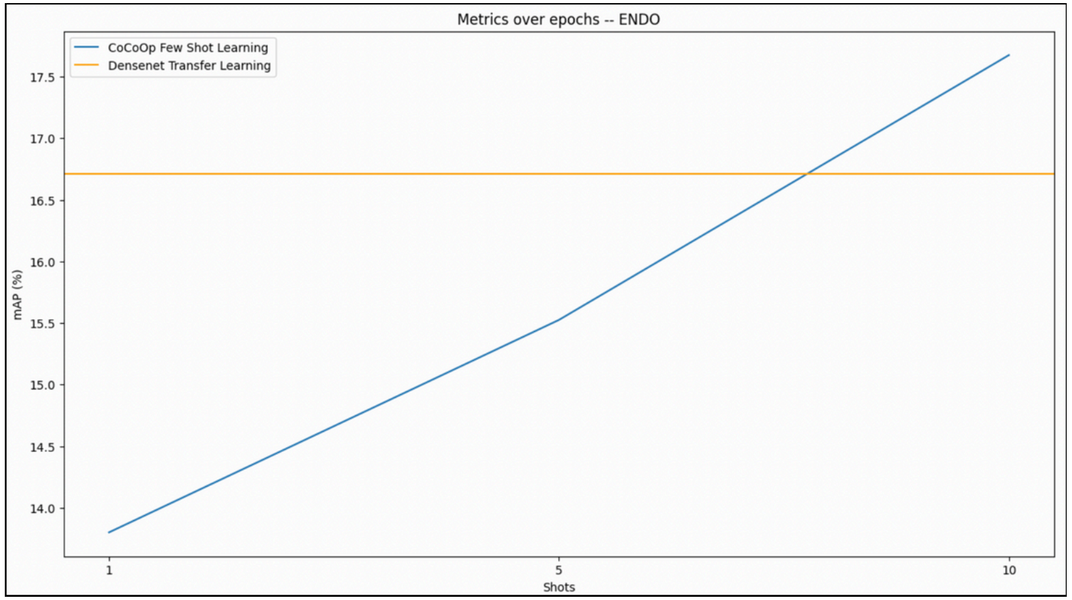


Experiment and Result - Endo







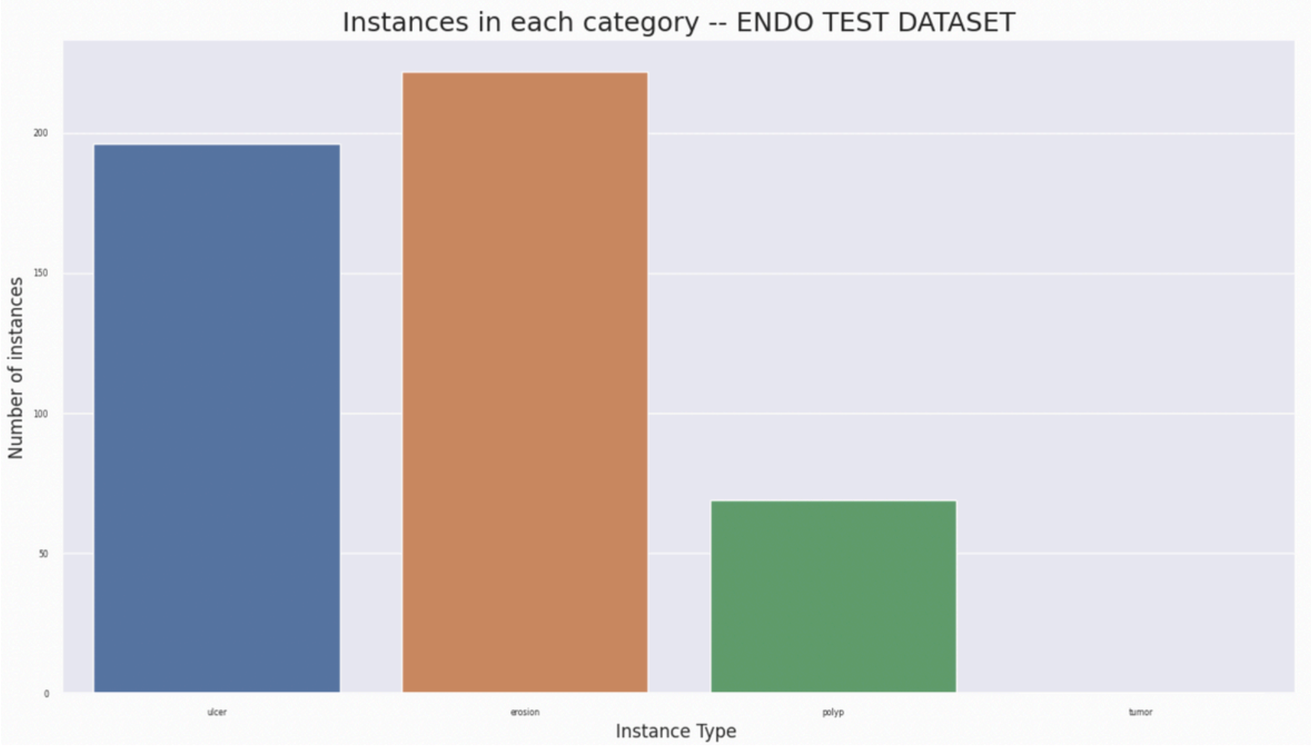


Conclusion

1. Discussion
2. Future Work

Conclusion - Discussion

- **Distribution of labels in Endo test data**
  - Analyzing the label distribution in the Endo test data reveals frequency and co-occurrence patterns, highlighting imbalances and informing improvements in model training and evaluation.



Conclusion - Future Work

- **Validate Prompt Engineering**
  - Conduct ablation tests to validate prompt engineering components.
- **Explore Advanced Visual Tuning**
  - Replace CoCoOp with specialized methods like DualCoOp and TAI++ for better multilabel classification.
- **Use Experiment Tracking Tools**
  - Utilize tools to record and manage experimental results for better reproducibility and comparison.
- **Apply Grad-CAM**
  - Use Gradient-weighted Class Activation Mapping (Grad-CAM) to visualize important image regions affecting model predictions.

Dataset	Prompt
Chest	A chest X-ray with thoracic disease {}.
Colon	A tissue slide of pathological tissue patches with {}.
Endo	A colonoscopy image with abnormalities {}.