

1 Description

Dataset name	The Hyper Kvasir Dataset
Link	Kaggle
License	CC BY 4.0
Medical discipline	Gastroenterology
Medical procedure	Endoscopy
Multi-class problem	✓
Multi-label problem	✗

This is the code repository for the Hyper-Kvasir dataset which is the largest publicly released gastrointestinal tract image dataset. In total, the dataset contains 110,079 images and 373 videos where it captures anatomical landmarks and pathological and normal findings. The results is more than 1,1 million images and video frames all together. The paper describing the data can be accessed [here](#).

This summary describes the identification of anatomical landmarks in the *lower GI tract*. Classes are:

- cecum
- ileum
- retroflex-rectum

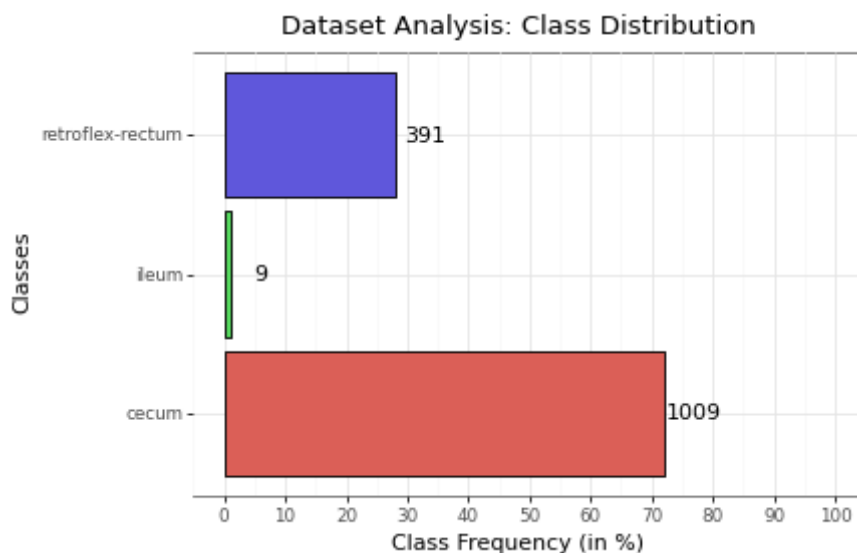


Figure 1: Class distribution: The Hyper Kvasir Dataset(Lower GI tract)

2 Pre-processing

For the purpose at hand, a sub-set of this dataset was used, to tackle the anatomical landmark classification. This dataset provides labeled images for both the lower and upper GI tract. They are treated as two separate classification tasks. In this summary, the classification of the landmarks in the *lower GI tract* is described.

3 Training

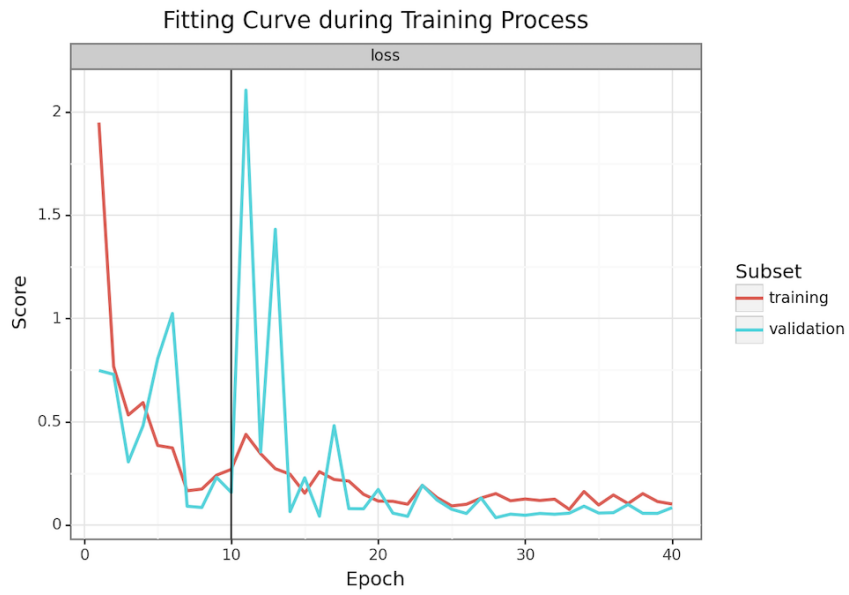


Figure 2: Training: The Hyper Kvasir Dataset(Lower GI tract)

When transfer learning is applied, a peak in training and validation loss after unfreezing of the model's weights, is common. In this instance, the validation loss is very high between episodes ten and 15. The unfreezing in combination with the high class imbalance can be an explanation for that. Other than that, the training curve 2 shows a good reduction in training and validation loss.

4 Results



Figure 3: Metric overview: The Hyper Kvasir Dataset(Lower GI tract)

F1 score shows a great classification performance for the two well represented classes retroflex-rectum and cecum. The ileum class that consist of nine images in total (see figure 1), shows a mediocre performance of approximately 40 %.

The low *false positive rate* for ileum reflects, that samples from other classes are rarely classified as ileum. That means, our model can easily identify classes retroflex-rectum and cecum. The challenge seems to lie in the ileum class itself. Both scores might improve in a classification task with a more balanced dataset.

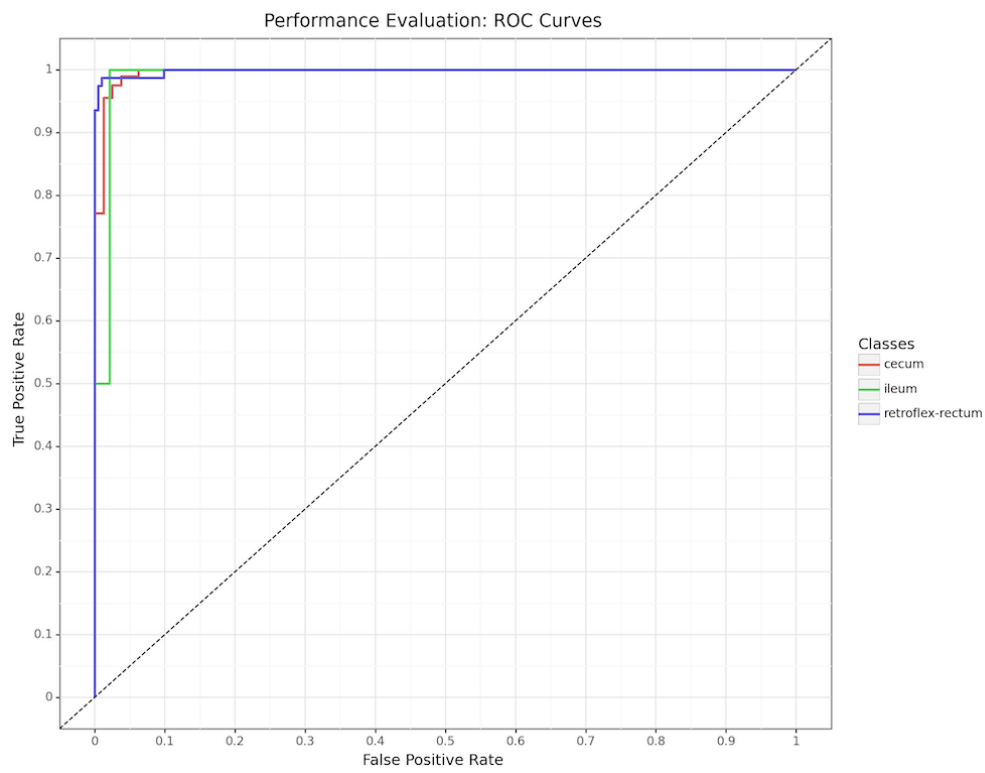


Figure 4: ROC curve: The Hyper Kvasir Dataset(Lower GI tract)

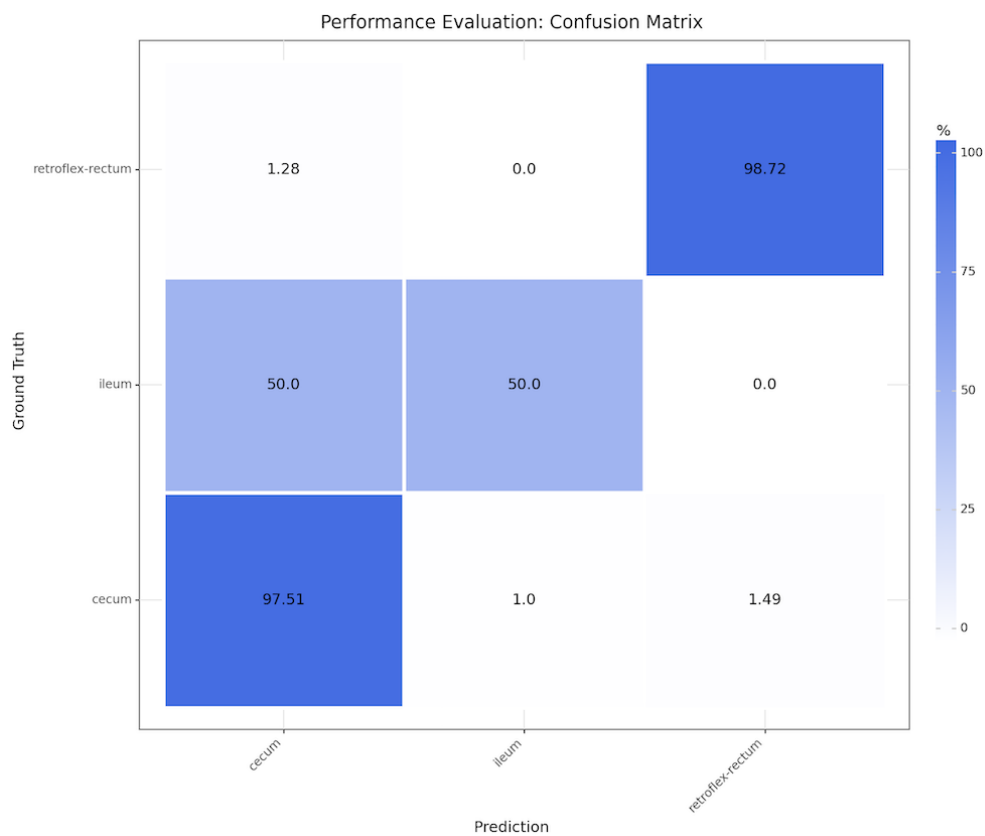


Figure 5: Confusion matrix: The Hyper Kvasir Dataset(Lower GI tract)

5 XAI

During medical procedures like GI endoscopies, instruments may appear on medical images. Explainability provides a valuable insight, if in fact the tissue, not the instrument is recognized by the model.

With that in mind, image **5142b571-4439-4841-af47-642e7bb37d28** is of interest, because it displays a medical instrument surrounded by tissue. The corresponding Grad-CAM image reveals, that the tissue close to the medical instrument is highly relevant to the model.

The other two sample images are not displaying any medical instrumentation. Their Grad-CAM images show that camera-close tissue is relevant to the model.

Image: 5142b571-4439-4841-af47-642e7bb37d28

Class: retroflex-rectum

Classified as: retroflex-rectum (99.3 %)

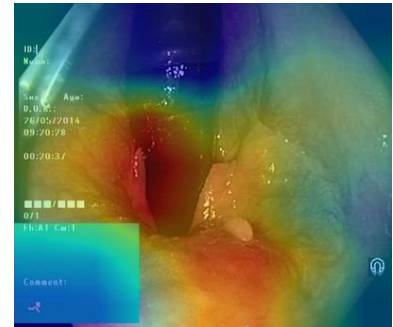
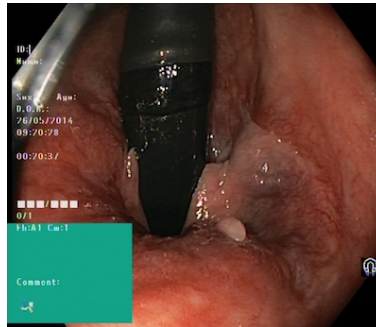


Image: b58d63e6-a1cc-4aa4-965d-7a6ae2f0c761

Class: cecum

Classified as: cecum (72.6 %)

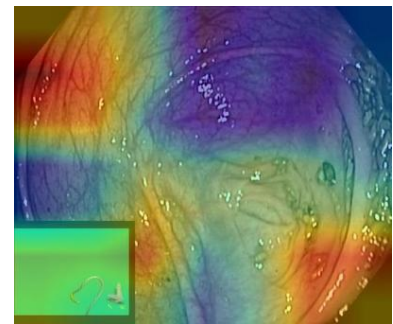
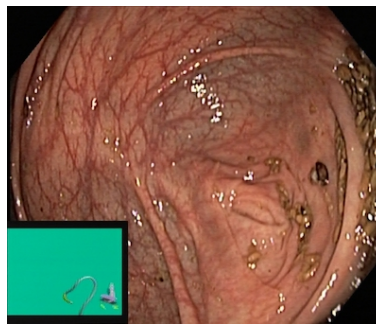
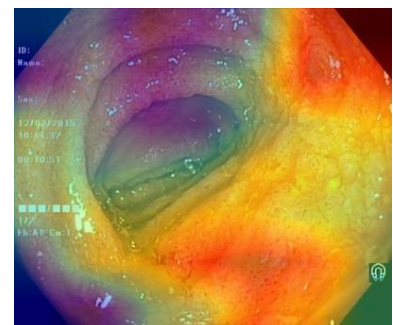
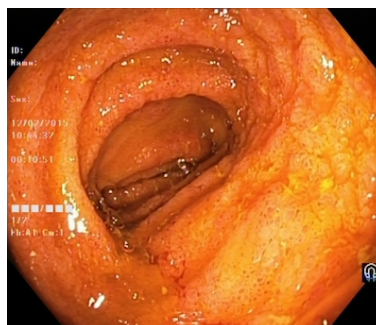


Image: c43d6d92-0b9a-4ea2-8241-a93213cec4a1

Class: ileum

Classified as: ileum (95.1 %)



6 Summary

Identifying anatomical landmarks using image classification is an interesting use case. AUCMEDI handles this challenge well: The noticeable imbalance among classes does impact the F1 score, but the ROC curve shows a solid classification capability for all classes.

Explainability of such a task is crucial, since medical instruments may constitute a distraction to the model. It is satisfactory to see, that in this instance the model seems to decide based on the tissue's structure.