Deep Learning Algorithms for Tissue Identification in Hysteroscopies

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Introduction

- In operative hysteroscopy, the doctor has to be careful not to hit the uterine tissue.
- This can cause several problems, including a very serious uterine perforation (reported between 0.12 to 3% in Germany [1], Holland [2], and France [3]).
- Related complications: severe bleeding, damage to the intestine, bladder and ureters, which usually requires additional surgical procedures and long-term treatment.
- **Key idea:** Automated image classification, to distinguish normal endometrial, endometrial polyps and myometrial tissue.

Objective

- Design a deep learning algorithm (for having excellent results on similar problems [4] [5]) that uses patient images to identify uterine tissues, as identical problems performed excellent results;
- Test the performance of the proposed algorithm on clinical data.

Methodology

Materials

Were collected:

➔ 270 images of size 720 x 576 were collected from 25 patients during hysteroscopy exams performed in an outpatient clinic (OC) scenario;

➔ 230 images were extracted from 11 videos of resolution 1440 x 1080 recorded during hysteroscopy exams performed under general anaesthetic (GA) in the operating room.

The images were divided into 2 classes by an experienced gynaecologist:

- Normal endometrial tissue (Figure 1);
- Endometrial polyps (Figure 2).

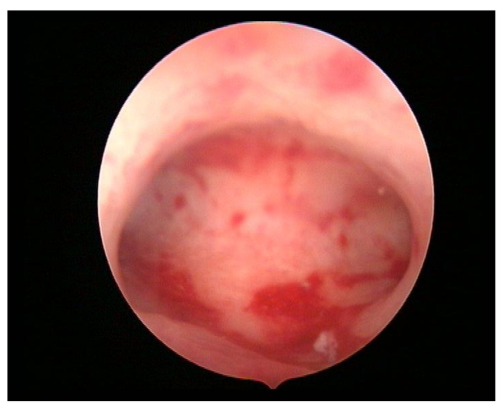

Figure 1: Example of image of normal endometrium tissue.

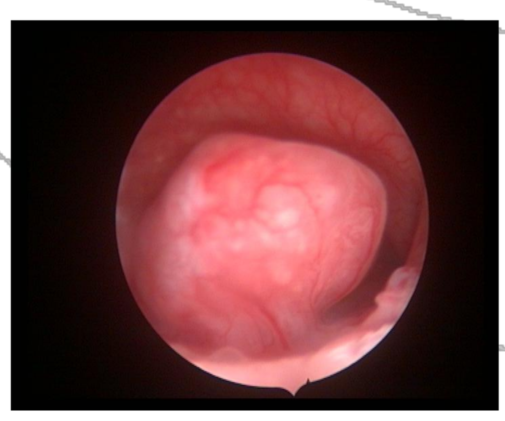

Figure 2: Example of image of endometrial polyp.

Tissues	Nº of images	Cropped images	Nº of patients
Normal endometrial	140+100	1000	13+8
Endometrial polyp	130+120	1000	12+7

Table 1: Division of images into normal endometrial tissue and endometrial polyp classes

CNN architectures and training

- Two different convolutional neural network architectures were considered:
  - VGG-16;
  - ResNet-50.
- Three transfer learning techniques were applied and compared:
  - Feature extraction and fully connected layers (FE+FC);
  - Feature extraction and support vector machines (FE+SVM);
  - Fine tuning of convolutional and fully connected layers (FT+FC).
- Two classifications
  - Fully automatic: the algorithm receives an image and classifies it automatically without human intervention;
  - Semi automatic: relevant portions of the image are first extracted by the operator and then classified by the algorithm.
- All networks were trained for 50 epochs, using the Adam optimizer with learning rate 0.0001 and mini-batch size of 32. Additionally, a dropout of 0.4 was used in two layers for each network, between the fully connected layers.

- The images in the dataset were randomly divided into 80% training images and 20% test images, guaranteeing that images from patients in the test set could not be included in the training set.
- The classification performance is evaluated using the following metrics: accuracy, precision, recall, and F1-score.

Results

Fully-automatic classification

For this classification five transformations were applied to each image (data augmentation technique) including rotations, mirroring, zoom, and brightness level adjustment. The results are obtained in the Table 2.

	VGG-16			ResNet-50		
Metrics	**FE+FC**	**FT+FC**	**FE+SVM**	**FE+FC**	**FT+FC**	**FE+SVM**
Accuracy	0.67	0.54	0.64	0.70	0.74	0.70
Precision	0.69	0.52	0.60	0.70	0.67	0.64
Recall	0.62	0.90	0.86	0.70	0.94	0.92
F1-score	0.65	0.66	0.70	0.70	0.78	0.75

Table 2: Comparison of different transfer learning techniques applied to the VGG-16 and ResNet-50 architectures for the fully-automatic classification.

Semi-automatic classification

The dataset for this classification task was generated from the previous dataset (500 images from 40 patients) by cropping four different significant portions from each image (Figure 3). The results are obtained in the Table 3.

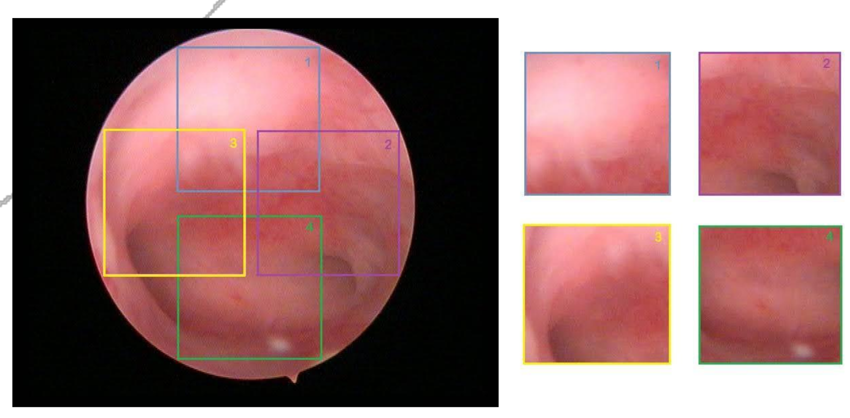

Figure 3: Example of portions cropped from the original image.

	VGG-16			ResNet-50		
Metrics	**FE+FC**	**FT+FC**	**FE+SVM**	**FE+FC**	**FT+FC**	**FE+SVM**
Accuracy	0.96	0.93	0.92	0.95	0.95	0.96
Precision	0.97	0.89	0.89	0.92	0.92	0.94
Recall	0.94	0.97	0.96	0.99	0.98	0.99
F1-score	0.96	0.93	0.93	0.96	0.95	0.97

Table 3: Comparison of techniques in the transfer learning application to the VGG-16 and ResNet-50 architecture for the semi-automatic classification.

Conclusions

- The problem of classifying images obtained from an hysteroscopy exam using CNN-based classifier was considered.
- Different network architectures and transfer learning techniques were tested to discriminate normal endometrial tissue images from endometrial polyps.
- In the fully-automatic classification of hysteroscopy images, the use of fine tuning on a ResNet-50 architecture pre-trained over the ImageNet dataset is shown to provide interesting classification results even with little data variability.
- Classification of pre-selected portions cropped from the original images is shown to be reliably performed even with such a small training dataset, due to the reduced variability of the considered samples.

References and acknowledgements

1. Burkhard Aydeniz et al. A multicenter survey of complications associated with 21 676 operative hysteroscopies. *European journal of obstetrics, gynecology, and reproductive biology*, 104:160–4, 10 2002. doi: 10.1016/S0301-2115(02)00106-9.
2. Frank William Jansen et al. Complications of hysteroscopy: a prospective, multicenter study. *Obstetrics and gynecology,* 96 2:266–70, 2000.
3. Aubert Agostini et al. Risk of uterine perforation during hysteroscopic surgery. *The Journal of the American Association of Gynecologic Laparoscopists*, 9:264–7, 08 2002. doi: 10.1016/S1074-3804(05)60401-X.
4. Peng-Jen Chen et al. Accurate classification of diminutive colorectal polyps using computer-aided analysis. *Gastroenterology*, 154, 10 2017. doi: 10.1053/j.gastro.2017.10.010.
5. Zhen Ding et al. Gastroenterologist-level identification of small bowel diseases and normal variants by capsule endoscopy using a deep-learning model. *Gastroenterology*, 2019.

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