A new dataset of distortions on Wireless Capsule Endoscopy Images for pathological ifentification

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Overview

Objectives

The main objective of the project is to develop a smart system for:

- Identify the pathological finding on wireless capsule endoscopy (WCE) images
  - Including a pre-processing module that aims at improving the quality of the acquired images
  - Develop a set of image quality enhancement solutions based on kinds of distortion

There are **many kinds of distortion** & in **different levels**

Context

Alert

Colorectal cancer is a major health problem.

1 Bray F, Ferlay J, Soerjomataram I, Siegel RL, Torre LA, Jemal A, "Global cancer statistics 2018: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries", CA Cancer J Clin. 2018 Nov; 68(6):394-424.

2 Santé Publique France, https://www.santepubliquefrance.fr/maladies-et-traumatismes/cancers/cancer-du-colon-rectum

3 McKESSON, "Colorectal Cancer & Laboratory Screening", 2018

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Colorectal cancer is a major health problem.

Example

In 2018, the Colorectal cancer (CRC) is the third (second respectively) leading cause of cancer death in the world (France, respectively).[1,2]

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Solution

Studies have shown that early detection can result in up to a **92% survival rate for stage I of cancer.**[3]

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Wireless Capsule Endoscopy

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Wireless capsule endoscopy include its **non-invasive** character and its ability to visualize proximal and distal parts of the intestine

Challenges

- Some common acquisition distortions (**noise**, **blur**, **uneven illumination**, **specular reflection**) may affect the WCE based diagnosis.

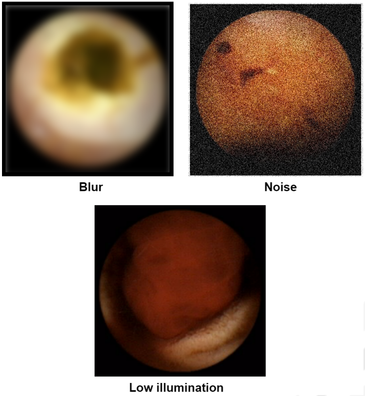

Figure 1: Illustration of some common WCE images distortions

Algorithm

input : *distorted_image*
output : *enhanced_image*

$types\_distortion = \text{classifier}\ (distorted\_image)$;
for *type* **in** *types_distortion* **do**
    $enhanced\_image \leftarrow \text{enhancer}_{type}\ (distorted\_image)$
end
return *enhanced_image*

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Requirement:

Create the $\boxed{\text{classifier}}$ and $\boxed{\text{enhancer}_{type}}$

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Creating a dataset is the **most important** thing to do

Existing datasets

Table 1: An overview of existing GI datasets.

Dataset	Findings	Size
CVC-356 [1]	Polyps	356 images
CVC-ClinicDB (also named CVC-612) [2]	Polyps	612 images
CVC-VideoClinicDB (also named CVC-12k) [1]	Polyps	11954 images
CVC-ColonDB [1]	Polyps	380 images
Endoscopy Artifact detection 2019 [3]	Endoscopic Artifacts	5,138 images
ASU-Mayo polyp database [4]	Polyps	18,781 images
ETIS-Larib Polyp DB [5]	Polyps	196 images
KID [6]	Angiectasia, bleeding, inflammations, polyps	2371 images and 47 videos
GIANA 2017 [7]	Polyps & Angiodysplasia	3462 images and 38 videos
GIANA 2018 [8]	Polyps & Small bowel lesions	8262 images and 38 videos
GASTROLAB [9]	GI lesions	Some 100s of images andfew videos
WEO Clinical Endoscopy Atlas [10]	GI lesions	152 images
GI Lesions in Regular Colonoscopy Data Set [11]	GI lesions	76 images
Atlas of Gastrointestinal Endoscope [12]	GI lesions	1295 images
El salvador atlas of gastrointestinal video endoscopy [13]	GI lesions	5071 video clips
Kvasir [14]	Polyps, esophagitis, ulcerative colitis, Z-line,pylorus cecum, dyed polyp, dyed resection margins, stool	8000 images
Kvasir-SEG [15]	Polyps	1000 images
Nerthus [16]	Stool - categorization of bowel cleanliness	21 videos

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Using **HyperKvasir** [17] dataset

HyperKvasir dataset

Table 2: Overview of the data records in the HyperKvasir dataset.

Data Record	# Files	Description
Labeled images	10,662 images	23 classes of findings
Segmented Images	1,000 images	Segmentation masks for polyp findings
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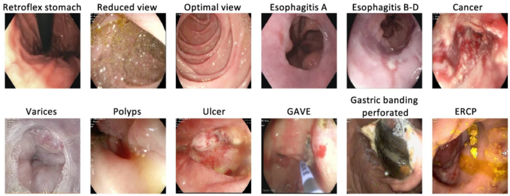
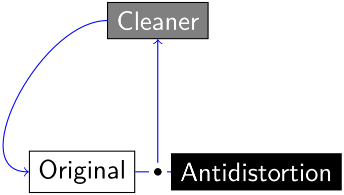


Figure 2: Image examples of the various labeled classes for images and/or videos.

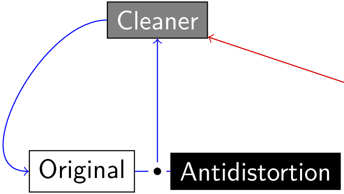
Ourwork



a) Clean the image

Step 1 Cleaning the existing distortion in HyperKvasir dataset

Ourwork



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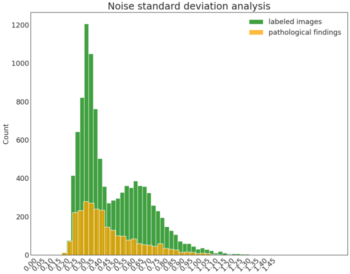

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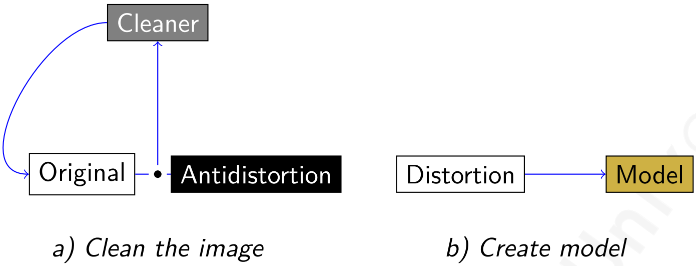
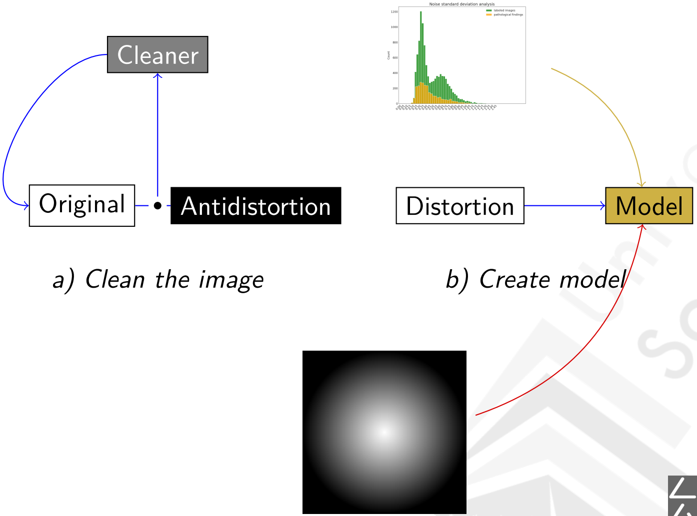


Step 2 Creating the model to generate the new artificial distortions

Ourwork

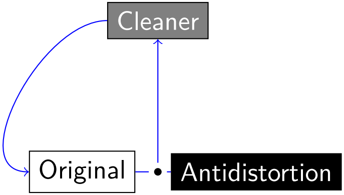


a) Clean the image

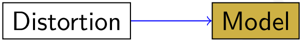
b) Create model

Ourwork

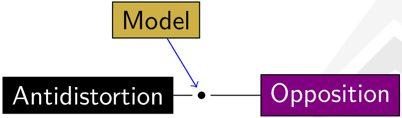
Step 3 Add the new artificial distortions to the antidistorted images



a) Clean the image



b) Create model



c) Add artificial distortion

Results

In this stage, we have to clean the existing distortion in the HyperKvasir dataset.

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Original Image → Denoising

Results

In this stage, we have to clean the existing distortion in the HyperKvasir dataset.

Original Image → **Denoising** → Debluring

Results

In this stage, we have to clean the existing distortion in the HyperKvasir dataset.

Original Image → Denoising → Debluring → Uneven Illumination Correction

Results

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Original Image → Denoising → Debluring → Uneven Illumination Correction → Specular Reflection Removal

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Original Image → Denoising → Debluring → Uneven Illumination Correction → Specular Reflection Removal → Antidistorted Image

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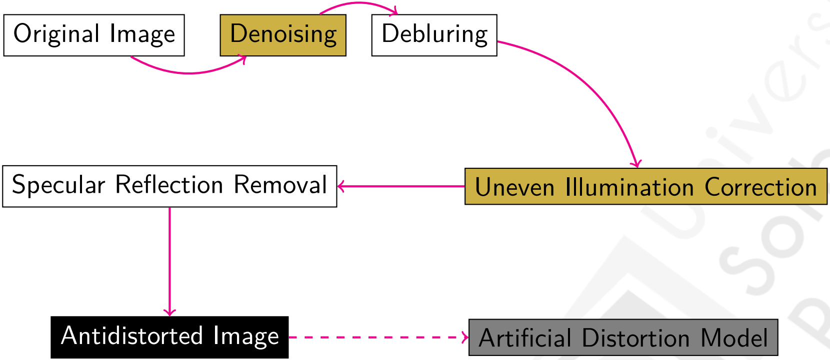
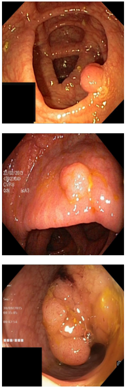


Results

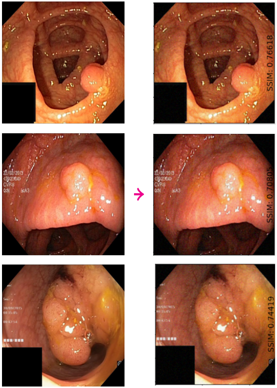
- Noise



a) Original

Results

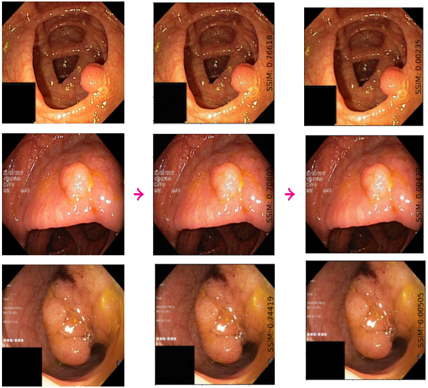
- Noise



a) Original *b) Noisy*

Results

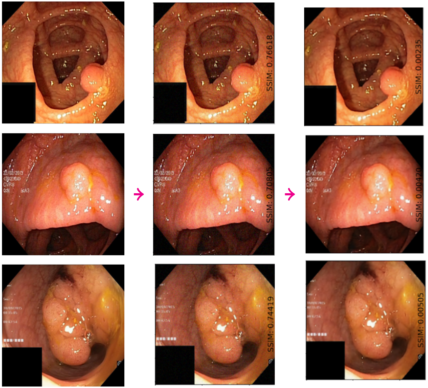
- Noise



a) Original *b) Noisy* *c) Denoised*

Results

- Noise



a) Original *b) Noisy* *c) Denoised*

		Noisy-image	C-BM3D	NM-Mean	CAE
σ_n	0.25	0.8095	0.7364	0.9068	**0.9158**
	0.3	0.7561	0.7275	0.8884	**0.9097**
	0.35	0.7084	0.7106	0.8752	**0.9033**
	0.4	0.6615	0.7039	0.8614	**0.8991**
	0.6	0.5102	0.6517	0.8222	**0.8766**
	0.65	0.4810	0.6428	0.8132	**0.8681**
	0.7	0.4508	0.6389	0.8051	**0.8661**

d) Comparison using mean SSIM for different level where $n \sim N(0, \sigma_n^2)$

Results

- Noise

Table 3: Comparison using mean SSIM for different level where $n \sim N(0, \sigma_n^2)$

	σ_n						
	0.25	0.3	0.35	0.4	0.6	0.65	0.7
Noisy-image	0.8095	0.7561	0.7084	0.6615	0.5102	0.4810	0.4508
C-BM3D	0.7364	0.7275	0.7106	0.7039	0.6517	0.6428	0.6389
NM-Mean	0.9068	0.8884	0.8752	0.8614	0.8222	0.8132	0.8051
CAE	**0.9158**	**0.9097**	**0.9033**	**0.8991**	**0.8766**	**0.8681**	**0.8661**

Table 4: Comparison using mean PSNR for different level where $n \sim N(0, \sigma_n^2)$

	σ_n						
	0.25	0.3	0.35	0.4	0.6	0.65	0.7
Noisy-image	32.89	31.44	30.34	29.32	26.37	25.85	25.22
C-BM3D	27.51	27.52	27.47	27.47	27.28	27.21	27.16
NM-Mean	**35.81**	**34.74**	**34.12**	**33.48**	**31.85**	**31.51**	31.14
CAE	32.28	32.56	32.70	32.38	31.42	31.18	**31.43**

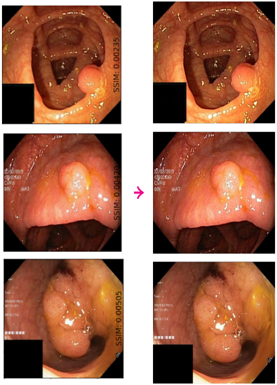
Results

- Blur

a) Denoised

Results

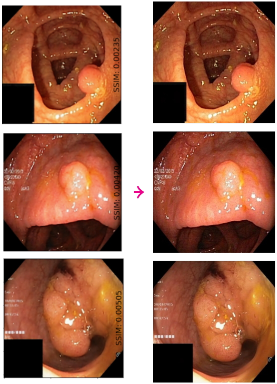
- Blur



a) Denoised *b) Deblurred*

Results

- Blur



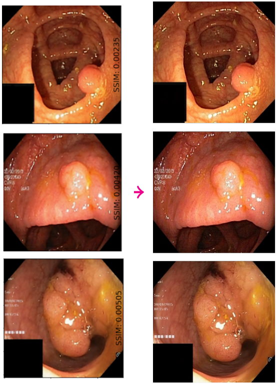
a) Denoised *b) Deblurred*

$$index = var(\mathcal{L}(f(x,y)))$$

Apply the ***variance of the Laplacian****[18] method to your own photos to detect the amount of blurring.*

Results

- Blur



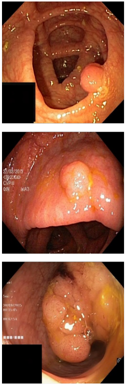
a) Denoised *b) Deblurred*

	Denoised-image	Deblured- mage
First exp	378	501
Second exp	321	428
Third exp	224	367

The variance Laplacian Index before and after deblurring.

Results

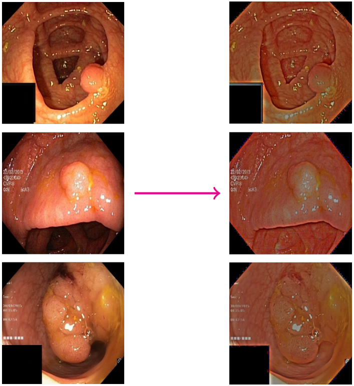
- Uneven Illumination



a) Deblurred

Results

- Uneven Illumination

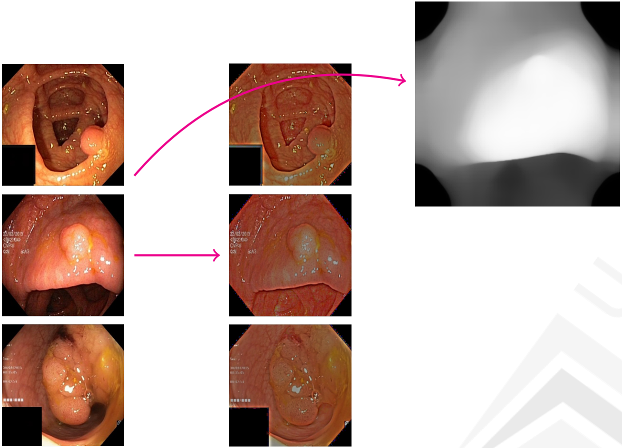


a) Deblurred

b) Uneven Illumination Correction

Results

- Uneven Illumination

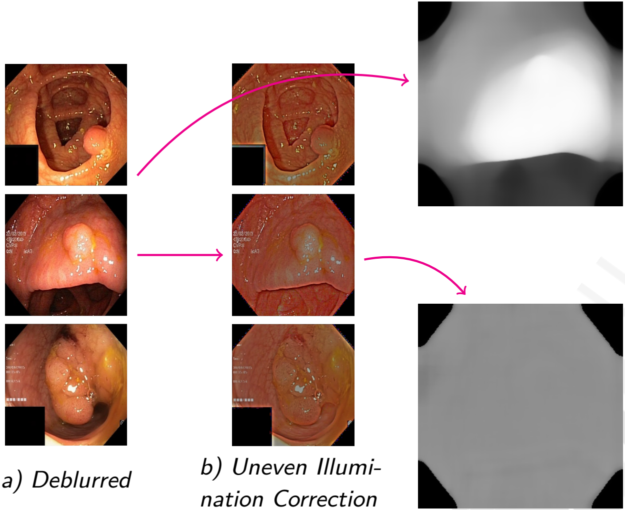


a) Deblurred

b) Uneven Illumination Correction

Results

- Uneven Illumination

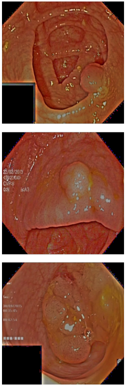


a) Deblurred

b) Uneven Illumination Correction

Results

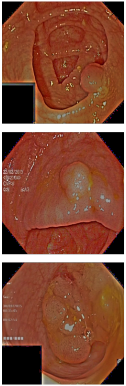
- Specular Reflection

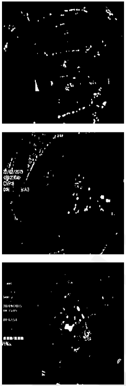


a) Uneven Illumination Correction

Results

- Specular Reflection

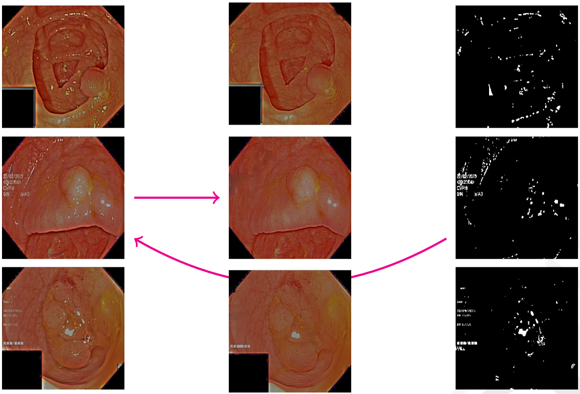




a) Uneven Illumination Correction

Results

- Specular Reflection



a) Uneven Illumination Correction

b) Specular Reflection Inpainting

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Thank you for watching!

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