Automatic Diagnosis Of Renal Pathologies Using Kidney Ultrasound Imaging

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The problem

- Renal pathologies have become a **major challenge** for health systems.
  - Lower-middle-income countries → 2 million people urgent need of dialysis.
  - Patients on renal replacement has doubled every decade since 1980.
  - The World Health Organization (WHO) estimates that only 10% of those in need undergo kidney transplantation annually.
- Ultrasound imaging (US) is routinely used as the first line of medical imaging
  - Advantages: real-time imaging, non-ionizing radiation, better cost effectiveness, portability...
  - Disadvantages: noise, artifacts, **operator dependence**...

Challenge: High intra-operator variability

US image analysis plays a critical role facing early stages of renal pathologies.

Objectives

1. Good primary care judgment.
2. Early detection and prevention.

How? CAD System

- CAD = Computer-Aided Diagnosis.
- Help clinicians to make decisions (primary care and specialists).
- Acts as a "second opinion".

Related Work

- Current applications of DL in US imaging:
  - Classification
  - Detection
  - Segmentation
- Several articles about DL in medical imaging, **but few focus on medical US.**
- DL has been **scarcely applied in kidney US images.**

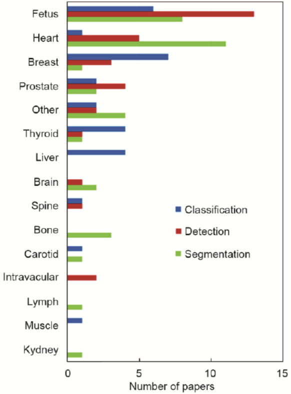

Figure: Applications of deep learning in medical ultrasound analysis [4]

Related Work

Nevertheless, there are some methods that have been used for detecting kidney abnormalities:

Analysis and Identification of Kidney Stone Using K^{th} Nearest Neighbour (KNN) and Support Vector Machine (SVM) Classification Techniques[1]

Jyoti Verma*, Madhwendra Nath, Priyanshu Tripathi, and K. K. Saini
Department of ECE, Hindu College of Engineering Industrial Area, Sonepat, Haryana, India 131001
**e-mail: er.jyotiverma01@gmail.com*

Detection of Renal Calculi in Ultrasound Image Using Meta-Heuristic Support Vector Machine

S. Selvarani[1] · P. Rajendran[2]

Automatic Detection of Renal Abnormalities by Off-the-shelf CNN Features

Priyanka Kokil & S. Sudharson

Abnormality Detection in the Renal Ultrasound Images using Ensemble MSVM Model

S. Sudharson[1] and Priyanka Kokil[2]

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Related Work

An ensemble of deep neural networks for kidney ultrasound image classification

S Sudharson, Priyanka Kokil*

Department of Electronics and Communication Engineering, Indian Institute of Information Technology, Design and Manufacturing, Kancheepuram, Chennai 600127, India

The state-of-the-art methods vs our method

The state-of-the-art methods:

- **Multi-class** problem (mutually exclusive).
- 2 to 4 classes.

Our method:

- **Multi-label** problem (**NOT** mutually exclusive).
- 7 classes

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Data Description

The Nephrology Department from *Hospital Ramón y Cajal* provided us with a set of 1985 renal ultrasound images, consisting of 450 healthy and 1535 pathological kidneys.

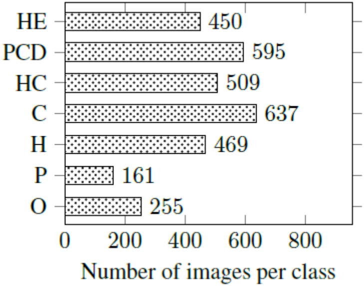

Figure: Number of images per class/pathology in the given dataset. (**HE**-Healthy, **PCD**-Poor Corticomedullar Differenciation, **HC**-Hyperechogenic Cortex, **C**-Cyst, **H**-Hydronephrosis, **P**-Pyramid, **O**-Others)

Data Description

Each image had its corresponding segmentation mask of the kidney and the bounding box coordinates of the local lesions.

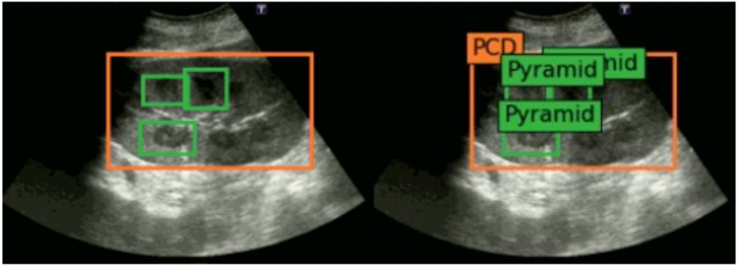

Figure: Annotation example. The image presents Poor Corticomedullar Differenciation (PCD) and Pyramids.

Proposed CAD System

1. Binary Image Classification (Healthy vs Pathological).
2. Multi-label Global Image Classification (Healthy vs 6 pathologies).
3. Local Object Detection:
   - Local detection of pathologies.
   - Aggregation of local detections into a global diagnosis.
4. Hybrid Classification by merging 2. and 3.

Proposed CAD System

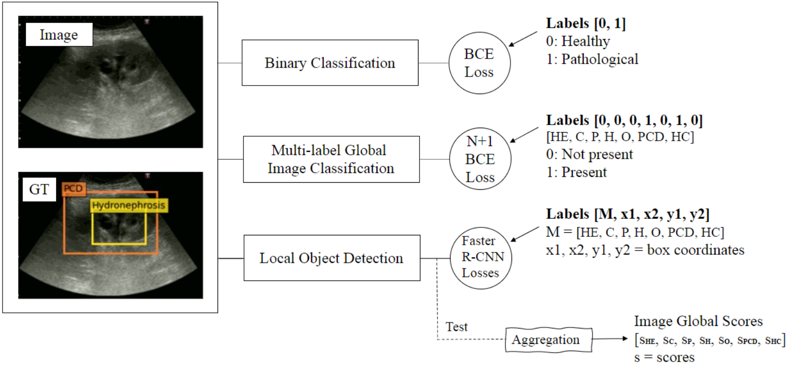

Figure: Schemes of binary classification, multi-label global image classification and local object detection for the proposed CAD system. Each approach is trained with the set of images, specific labels and different losses. The local object detection outputs go through an aggregation mechanism resulting in multi-label global image scores.

Proposed CAD System

Faster R-CNN

Two steps detector:

Step 1: over the whole image

- Backbone
- RPN

Step 2: over each ROI

- ROI Pooling
- Classifier
- Predict bounding box

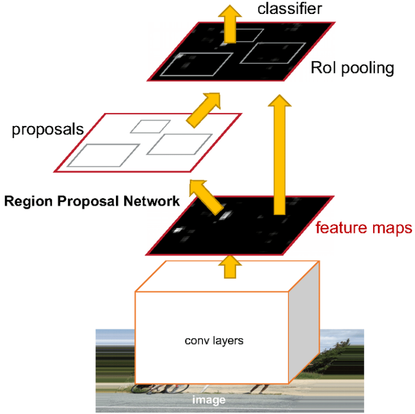

Figure: Faster R-CNN architecture [5]

Proposed CAD System

Aggregation mechanisms:

- *Max* aggregation

$$\boxed{\mathrm{Max}_k = \max_i (s_{ik})} \tag{1}$$

- *Area* aggregation

$$\boxed{\mathrm{Area}_k = \frac{1}{HW}\sum_i^{B_k} s_{ik}\, w_{ik}\, h_{ik}} \tag{2}$$

- *Sum* aggregation

$$\boxed{\mathrm{Sum}_k = \sum_i^{B_k} s_{ik}} \tag{3}$$

- *LSE* aggregation

$$\boxed{\mathrm{LSE}_k = \log\left(\sum_i^{B_k} \exp(s_{ik})\right)} \tag{4}$$

- *Mean* aggregation

$$\boxed{\mathrm{Mean}_k = \frac{1}{B_k}\sum_i^{B_k} s_{ik}} \tag{5}$$

- $k \in \{\mathrm{HE, C, P, H, O, PCD, HC}\}$; B boxes detected; s, w and h boxes' scores, width and height; H and W image's height and width.

Proposed CAD System

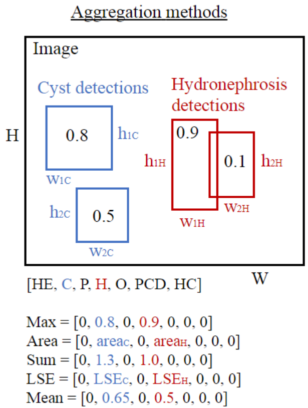

Figure: Example of how each aggregation method works.

$$\boxed{s_{hybrid} = s_{global} + \alpha s_{local}} \tag{6}$$

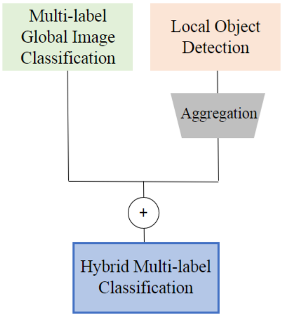

Figure: Proposed method for hybrid multi-label classification.

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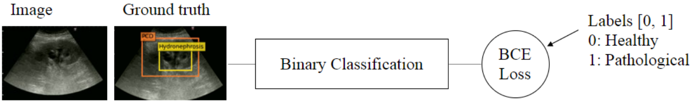
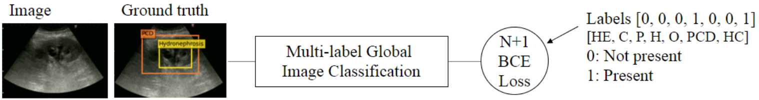
Binary Image Classification



Backbone		Healthy vs Pathological
AlexNet	AUC	0.7883
	SP-95	0.2681
ResNet50	AUC	**0.8472**
	SP-95	0.3363
EfficientNetB0	AUC	0.8281
	SP-95	**0.3451**
EfficientNetB1	AUC	0.8225
	SP-95	0.3121

Table: Different metrics in Healthy vs Pathological binary classification. The best scores are highlighted in bold.

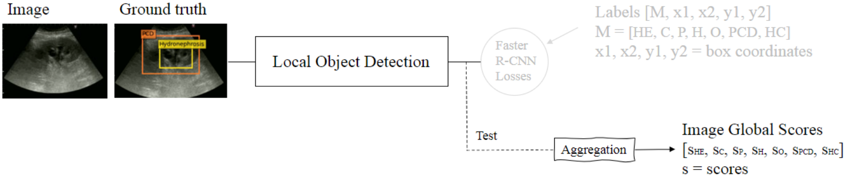
Multi-label Global Image Classification



Global	HE	PCD	HC	C	H	P	O	AVG
AUC	0.83	0.76	0.78	0.76	0.89	0.82	0.71	0.79

Table: Multi-label classification metrics based on Global Image Classification.

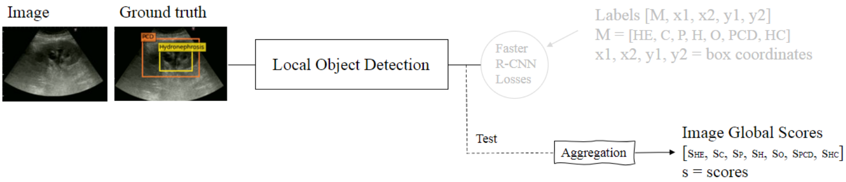
Multi-label classification based on Local Object Detection



	Max	Area	Sum	LSE	Mean	GIC
AUC	**0.783**	0.754	0.776	0.753	0.754	**0.793**

Table: Average AUC scores for the different aggregation methods for local classification. The Global Image Classification (GIC) average AUC is also present for comparison.

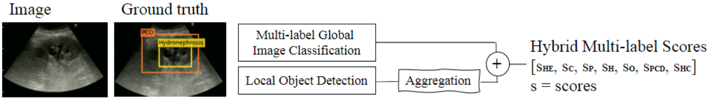
Multi-label classification based on Local Object Detection



AUC	HE	PCD	HC	C	H	P	O	AVG
Global	0.83	0.76	0.78	0.76	0.89	0.82	0.71	0.79
Local	**0.87**	0.47	**0.80**	**0.83**	**0.92**	**0.88**	0.70	0.78

Table: Multi-label classification average AUCs for Local Object Detection with *Max* aggregation. Those scores that overcome the previous global image classification are highlighted in bold.

Hybrid Multi-label Classification



AUC	HE	PCD	HC	C	H	P	O	AVG
Global	0.83	0.76	0.78	0.76	0.89	0.82	0.71	0.79
Local	0.87	0.47	0.80	0.83	0.92	0.88	0.70	0.78
Hybrid	0.89	0.72	0.83	0.85	0.93	0.90	0.75	0.84

Table: Multi-label classification metrics based on Hybrid approach with *Max* aggregation vs global and local classifications.

Global Overview

	Multi-label AUC	Binary AUC	Binary SP-95
Binary	-	0.8472	0.3363
Global	0.793	0.8401	0.3378
Local	0.7825	0.8904	0.4667
Hybrid	**0.8366**	**0.9017**	**0.4911**

Table: Global overview of the proposed methods for multi-label and binary classifications.

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Conclusions

- We proposed a CAD system for kidney US images, which may help both primary care and specialist nephrologists.
- Hybrid approach:
  - Binary AUC $= 0.9017$
  - Binary SP-95 $= 0.4911$
  - Multi-label AUC $= 0.8366$

Future work

Some improvements are possible and should be considered:

- Training the models only with kidney US images.
- Taking advantage of hybrid combination for the local object detection.

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Thanks for your attention